Analysis of Traffic Related Pollution Through Low Cost Mobile Air Quality Sensors

Thesis

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Abstract

Air pollution monitoring is often stationary and expensive, failing to provide easily accessible data in most nearby locations to where people live and work. In an age of technology, it should be possible to obtain this type of information to create a better understanding of health impacts associated with air pollution. The purpose of this investigation and analysis is to create a method of regular low-cost post-process mobile air quality sampling for Ohio State University's (OSU) campus using OSU's bus system, Campus Area Bus Service (CABS), as a mobile platform and locate highly concentrated areas of traffic emissions. These highly concentrated areas could be hazardous for students who are walking to class on a daily basis. Regular weekly data collection from the sensors will populate a program for overlaying the concentration of each pollutant on a map of the campus. Further analysis will reveal correlations between air quality and traffic activity, where conclusions can be drawn about the health impacts on students.

Acknowledgements

I would like to thank my advisor, Dr. Andrew May, for his patience, support, assistance, and for extending an invite to join his research team in 2015. I am extremely grateful.

I would like to thank Dr. Mark McCord, Dr. Rabi Mishilani, and Yangyang Zou for their interest, enthusiasm, and support during all steps of the project. I would like to thank and acknowledge Campus Area Bus System (CABS) , CampusParc for their flexibility and partnership, as well as Tyler LaSusa, Bennet Wildey, and Sachinda Liyanaarachchi for their contributions to this project in its initial stages. Without any of them, this project would not be possible. An additional thank you to Amlan Rath for his assistance in debugging code and teaching me ARCGIS.

Lastly I would like to thank my parents for always supporting me, for encouraging me to strive for greatness, and for being my motivation in life.

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Introduction

The phrase “air pollution” paints a mental image of dark, hazardous-looking plumes billowing out from an industrial landscape. This is often portrayed in entertainment, the media, and even textbooks. The everyday person may not think twice about their air they breathe on their way to work or school, the air looks clear to the naked eye so there is no cause for alarm. What the naked eye cannot see is the billions of gas particles circling can impact quality of life, health and mortality. The World Health Organization estimated ambient air pollution was the cause of 3 million premature deaths in cities and rural areas in 2012 (World Health Organization). Air pollution can increase the risk of cancer and both acute and chronic respiratory illness, as well as contribute to global climate change (World Health Organization; Hasenfratz et al.)

The National Ambient Air Quality Standards (NAAQS) have been established by the U.S. Environmental Protection Agency (USEPA) to protect human health and well-being. The USEPA monitors air quality to comply with NAAQS using stationary sites. These sites are sparse, with a small number of sites representing broad geographic areas. Existing methods of air quality sampling include chemiluminescence for oxides of nitrogen (NO_X), infrared absorption for carbon monoxide (CO), and ultraviolet absorption for ozone (O_3), all three using light intensity to approximate gas concentrations (Office of Environment and Heritage). These methods are highly expensive, around $10,000 per unit.

The USEPA uses the Community Multiscale Air Quality Modeling System (CMAQ) for predicting pollution, with a main focus on O_3 and particulate matter (PM) to estimate air pollution where measurements are unavailable. However, any outputs are based on model simulations fused with past air quality data from stationary sites and cannot provide a real-time measurement.

A study by Castell et al. looked at how low-cost sensors could contribute to overall, and ongoing, research on air quality. It looked at several different kinds of low-cost sensors, utilizing them in both the field and lab settings. Castell et al. found that performance varies from sensor to sensor, with worse performance in July. This was attributed to less traffic from most people taking vacations (Castell et al.). This is similar to one of the initial predictions of other projects utilizing low-cost sensors. The results conclude that while these types of sensors are not suitable for high performance, regulatory purposes, they are sufficient for providing aggregated air quality data to the public.

Engineering students at Massachusetts Institute of Technology (MIT) have also explored the idea of a low-cost air quality sensing network on their campus. In 2013, a team of students from various engineering disciplines created this sensing network for their senior project. Each air sensing unit has a relatively low cost (Balgobin et al.) and included sensors to measure CO, NOx, and O_3, as well as temperature and relative humidity. The network included stationary sensors at 24 different locations, and a few mobile sensors attached to university owned vehicles (Balgobin et al.). However, the team at MIT struggled with acquiring the mobile sensor's accurate Global Positioning System (GPS) location. They concluded that more work was needed to deem the mobile sensors as a success. It is important to note that MIT's campus, both in surface area and student population, is one sixth the size of OSU.

1.1. Objectives of this Work

In this work, we will use low-cost sensors to monitor air quality on OSU campus, located in Columbus, OH. Campus air quality is largely affected by vehicles; 83% of CO emissions in Columbus comes from mobile sources (United States Environmental Protection Agency, “National Emissions Inventory”). Approximately 38% of the 46,000 undergraduate students commute to campus by car (The Ohio State University Office of Student Life) and then walk to class; combined with the nearly 14,000 graduate and professional students and 32,000 faculty and staff, there is a total influx of roughly 63,000 commuters to campus on a daily basis. The air pollution associated with this traffic can affect not only the commuters but also the remainder of the undergraduate students that walk or bike to class from on or off campus housing. There is no current method of monitoring campus air quality, and therefore, no indication of the amount of student exposure to traffic-related pollution.

1.2. Significance

A greater understanding of air quality on OSU campus is needed, as many students are exposed to vehicle related emissions on a daily basis. There is no numerical “safe” level of air pollution exposure, but because of the health implications, it is recommended that strategies are needed to reduce individual daily intake (Good et al.). This project can help monitor air quality data for the OSU campus for the purpose of public awareness and for potential further use in carbon footprint reduction.

Methodology

2.1. Description of Sensor Package

A team was assembled in Fall 2015 to brainstorm logistics of mobile air quality sensors using CABS transit buses as mobile platforms. Initial work included choosing Alphasense air quality sensors, writing code for the data collection program, design of housing units, and testing data collection feasibility by attaching the sensing unit to a car.

The sensors that were needed as part of the original project proposal included O_3, NO_2, and CO. These three sensor requirements were used as a basis for research on potential sensor manufacturers. There were several factors that were important to the project; (a) cost, (b) sensitivity, and (c) compatibility. The team chose a Raspberry Pi for a control center and data storage. The sensors needed to be able to connect with the Pi in order to respond to the data collection code written by one of the team members. Alphasense sensors are high quality, in comparison to a "hobby" level air quality sensor. Cost, sensitivity, performance range, and linearity (the amount of error change) for each sensor can be seen below in Table 2.1. This table also includes both temperature and humidity range, important factors to consider since Ohio is a temperate climate. The sensors are electrochemical; a certain voltage is generated in the presence of an electrochemically active gas, this current is directly proportional to the amount of gas in ppm.

Table 2.1: Alphasense Sensor Parameters

Factor	CO Sensor	NO_2 Sensor	O_3 Sensor
Cost	$60.00	$70.00	
Sensitivity	220 to 375 nA/ppm in 2ppm CO	-175 to -420 nA/ppm at 2ppm NO_2	-200 to -425 nA/ppm at 1ppm O_3
Performance Range (ppm limit)	500	20	20
Linearity (ppm error)	Less than ± 1	Less than ± 0.5	Less than ± 0.5
Temperate Range (°C)	-30 to 50	-30 to 40	-30 to 40
Humidity Range (% rh)	15 to 90	15 to 85	15 to 85

The housing unit was constructed using sheets of acrylic, modeled through Solidworks, and cut using a laser cutter. Each unit had to be assembled like a puzzle, as the laser cutter can only cut two-dimensional shapes. The unit went through two prototype phases to ensure the sensors were receiving the required horizontal airflow. The first prototype was a very simple design, a box shape that can be seen in Figure 2.1 and the dimensions of this prototype can be seen in Table 2.2.

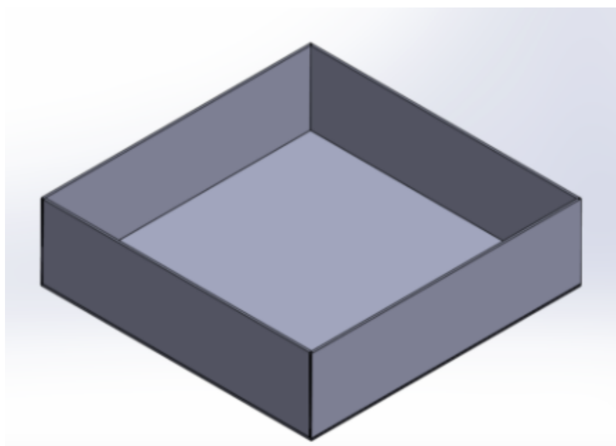


Figure 2.1: First Housing Prototype

Table 2.2: First Housing Prototype Dimensions

Housing Component	Dimensions (in)
Base	15.84 x 15.84
Sides (x4)	15.84 x 4.43

The large interior surface area of this first prototype allowed for numerous combinations of sensor layouts. However, this prototype did not include a roof, leaving the design inadequate as the sensors themselves are not waterproof and could be harmed during rainfall.

The most recent prototype incorporates aerodynamics and water-proofing. The front of the housing unit mimics the front of the bus in order to promote similar air flow as well as not to disrupt the airflow on the roof of the bus. As seen in Figure 2.2, the front of the housing unit is sloped at an angle to facilitate airflow through the housing unit and to provide shelter from rain.

Figure 2.2: Second Housing Prototype Side View without Roof

This second prototype was attached to a CABS bus in early spring semester of 2017. CABS initially allowed bolting the unit onto the roof; however, an alternative, non-invasive method of attachment had to be determined for future installations on the CNG buses. In order to prevent damage to the plastic, a 1/4th inch foam layer will be attached to the bottom of the unit. The intention of the foam is to absorb vibrations the unit may experience from the bus as well as a layer of protection or cushion if the bus goes over a bump in the road. The unit will be attached with high strength, poly-fiber chord, similar to the kind used for outdoor activities. The reason for the chord is to allow the unit small movements. If the unit is rigidly attached to the bus, the plastic could crack or shear due to unexpected forces such as vibrations from the bus traveling on a rough surface, or bouncing movement due to potholes.

2.2. Locating Sensors on Buses

To move forward, the optimal location on the bus for the sensing units had to be determined. Several constraints for determining location were the sensors requiring a perpendicular airflow for best results and method of housing attachment to the bus must be non-invasive to the buses' chassis. Many academics have reviewed aerodynamics of common public transportation models using computational fluid dynamics (CFD), and while this is not the main focus of study for this project, the results displayed in the literature proved very useful in determining this optimal location. In 2014, Takroni et al. used Ansys FLUENT to look at aerodynamics of bus models, with a velocity parameter of 100 km/hr (approximately 62 mph). It demonstrated that the velocity and pressure on the rear of the bus were low compared with the front of the bus, which is expected due to flow stagnation (Takroni, Radhwi, and Gawad). The results of the CFD analysis for the bus model is seen below in Figure 2.3a and Figure 2.3b respectively.

(a) (b)

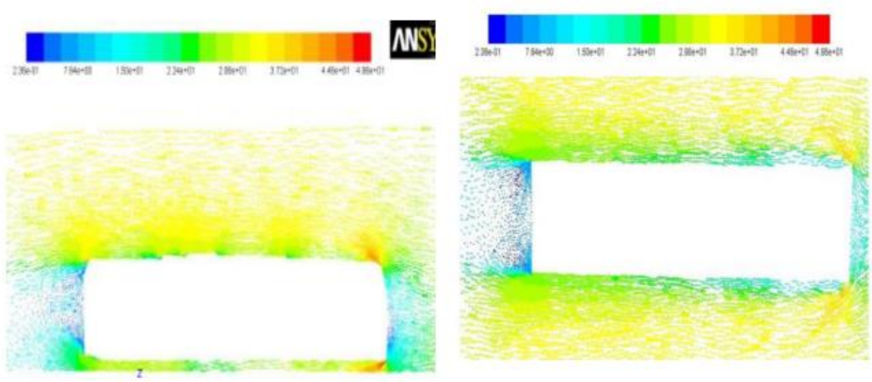


Figure 2.3: Velocity Vector of (a) Horizontal Section, (b) Turbulent View of Longitudinal Section[1]

1 1Takroni, Eyad Amen Mohamed, Muhammad N. Radhwi, Dr., and Ahmed F. Abdel Gawad, Dr. *Aerodynamic Characteristics and Drag Reduction of Buses.* Academia. N.p., 2014

These figures served as an approximation for CFD analysis of the old-style diesel CABS buses, which rarely get up to 62 mph in speed. The bus models analyzed in this study Green velocity vectors indicate a lower speed relative to the range of speeds available. Interpreting these results, it was decided that the back end roof of the bus was the optimal location for the sensor housing unit, in close proximity to the emergency escape hatch. This provides optimal air flow for sensors while reducing the probability of direct flow from the bus tail pipe which would be a variable factor and skew data. It also reduces the possibility of any wind resistance force removing the unit from the roof.

OSU’s Transportation and Traffic Management (TTM) implemented a Compressed Natural Gas (CNG) fueling station and the university added a total of ten CNG buses in October 2017 (Transportation and Traffic Management). Additional CFD analysis for the housing unit location was conducted as the CNG tanks alter the bus roof geometry.

Using Solidworks, a model of the cabs bus was created. Dimensions were determined using Figure 2.4, acquired from CABS, and an on-site visit to the TTM Office where we were allowed to take measurements of the CNG tanks on top of the bus (seen in Figure 2.5). Of course, these measurements were not exact; the CNG tank geometry has chamfered edges making it difficult to get a precise reading on the measuring tape. Figure 2.6 displays the CABS CNG bus model that was used for CFD analysis.

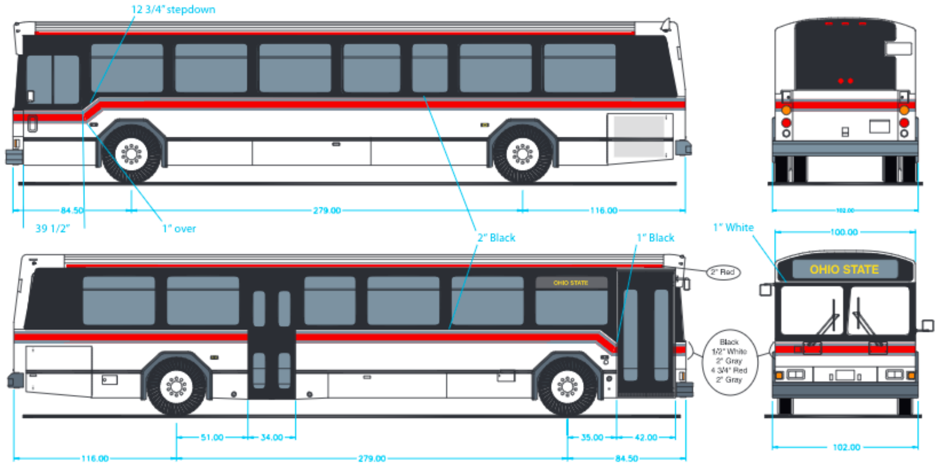


Figure 2.4: CABS Paint Dimensions

Figure 2.5: CABS bus CNG Tank Photos

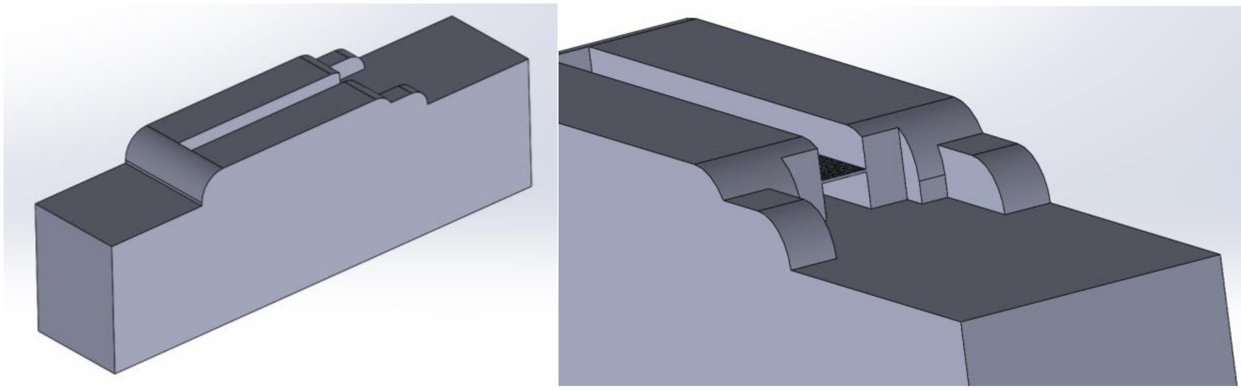


Figure 2.6: Solidworks Model of Bus and CNG Tank

This Solidworks model was run through the Ansys FLUENT program, simulating air flows around the CNG bus going approximately 15 mph. The area of interest is seen in Figure 2.6 above, the back end of the CABS bus on the grate between the CNG tanks. First the particle path lines were examined to determine if air flow perpendicular to the box could be achieved, as well as velocity magnitude. These two parameters are important to the functionality of the sensors; they required a perpendicular air flow. The velocity was checked to make sure the force was not so strong that the box would detach from the bus. The results of this CFD analysis are shown below. In Figure 2.7 the orthogonal view of the back of the bus is seen, the particle path lines are color coded based on a particle ID number. While the particles are densely populated over the small area of the bus roof grate, it is clear that along that way the airflow moves in a direction that would be perpendicular to the sensors if they are placed along the grate.

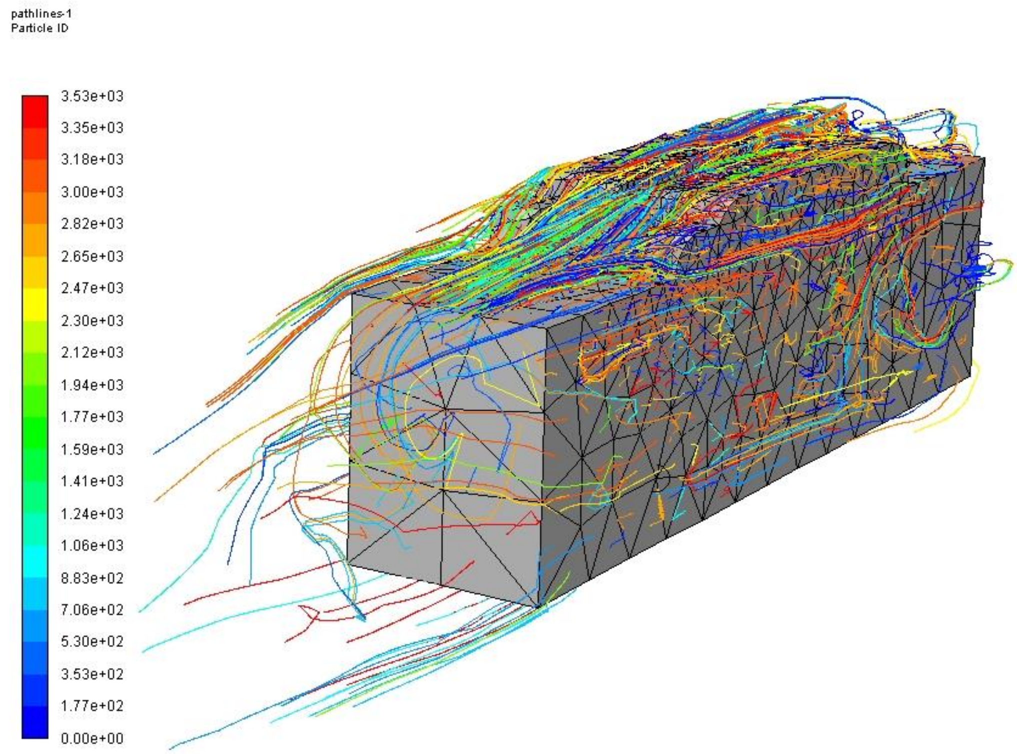


Figure 2.7: Particle Path lines on CABS CNG Bus

Next the velocity magnitudes surrounding the bus were calculated. These results can been seen below in Figure 2.8.

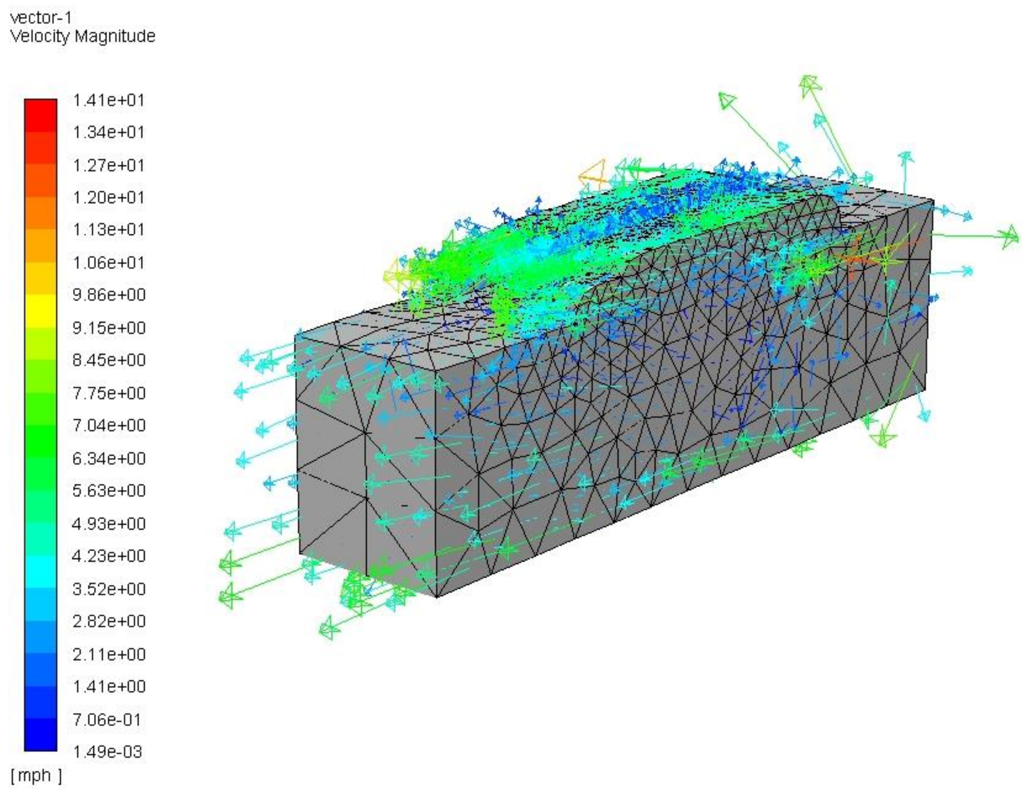


Figure 2.8: Velocity Magnitude on CNG CABS Bus

The surface area immediately surrounding the location of the box, bus roof, shows that on average the velocities in this region do not reach past 7 mph, similar to that of a human's walking speed, according to the figure's scale. In fact, it is evident that majority of the velocity on the bus roof is on the lower end of the scale. Based on the results from both figures, the housing unit's new location should be safe despite the altered roof geometry of the CABS bus.

2.3. Sampling Route for Data Collection

The CABS route of focus was chosen to be Campus Loop North (CLN); it is the most populated route and travels the main roads of campus. Prior to attaching the first unit to the CABS bus, test runs were performed by team members to test to accuracy of the sensors, the data collection code, and the geometry of the unit. The housing unit, sensors included was tied down to the roof of a personal automobile. During these data collection sessions, a team member would ride along in the car recording times at previously determined checkpoints corresponding with CLN bus stops, taking note of any unusual activity that could affect the air quality in the location (construction, nearby bus, etc.). These test runs were carried out for two semesters.

2.4 Considering Emissions Data Observed from CABS Bus with Traffic Data Observed from Garage Entries and Exits

There is currently only one sensing unit deployed on a CABS bus. Frequent outside factors affect the bus's ability to collect data on a daily basis, including regular bus maintenance. The bus data selected for this work are from March 21, March 22, March 23, March 29, April 10, May 9, May 11, and May 16 all from the year 2017. The sensors take a reading every three seconds and record the data in a text file stored on the Raspberry Pi. Data from the sensor units on CABS buses are combined with AVL data in MATLAB for analysis.

In order to investigate relationships between air quality data and traffic information, traffic data are needed. CampusParc, the company that manages on-campus parking, shared garage flow data per transaction for campus parking garages. Every time a car enters or exits a garage, the driver has to swipe their garage pass, collect a ticket, or pay for parking. Each entrance or exit is one transaction. These data acts as a proxy for campus-wide traffic, every transaction recorded by the garage is representative of one car driving on campus. A drawback to using these data as a proxy is that surface parking lots on campus are not accounted for, which provides a majority of parking space for commuter students. It is hypothesized that an increase in air quality sensor output will correspond to increases in traffic flows, and may help to explain the spatial distribution of air quality data by considering the flows from individual garages. An example data set from both the CABS sensing unit and CampusParc garages can be found in Appendix 4.1. In Figures 2.9, 2.10, 2.12 , and 2.13, the data from the sensors are plotted on top of campus car counts by hour (e.g., the total number of entries between 7:00 and 7:59 AM, etc.) from the garages for March 21, 2017. Plots for the other days can be seen in Appendix 4.2. In Figures 2.9 and 2.12, raw data from the sensors are plotted on top of hourly campus car counts from garages. In Figures 2.10 and 2.13, the average hourly sensor data are plotted on top of hourly campus car counts from garages. Figures 2.9 and 2.10 display CO concentration and Figures 2.12 and 2.13 display NO_2 and O_3 concentrations.

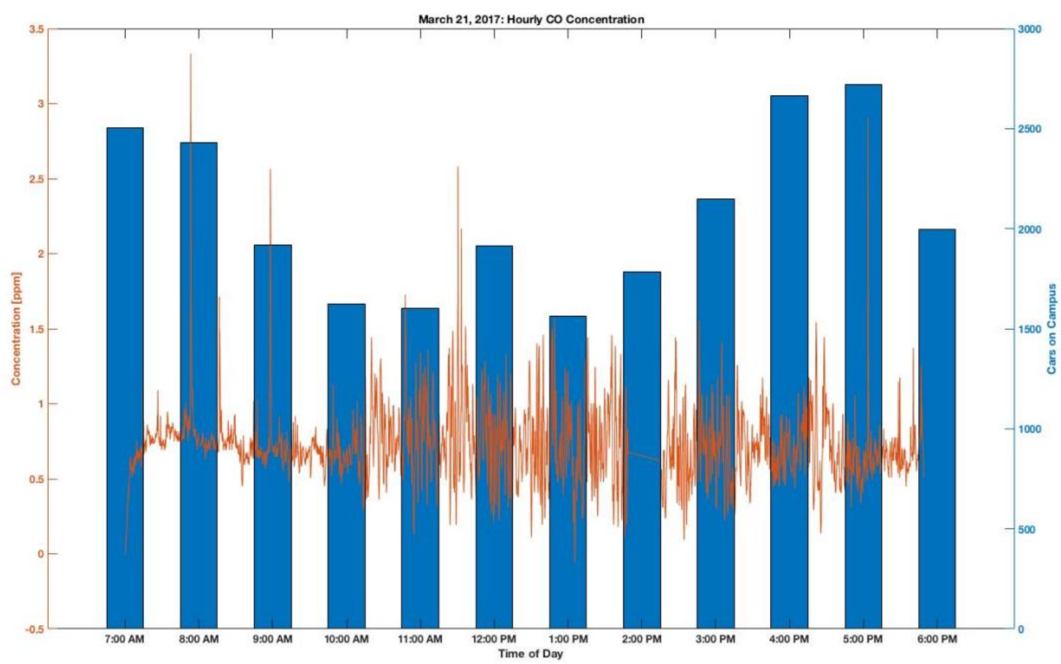


Figure 2.9: Hourly Carbon Monoxide Campus Levels for March 21, 2017

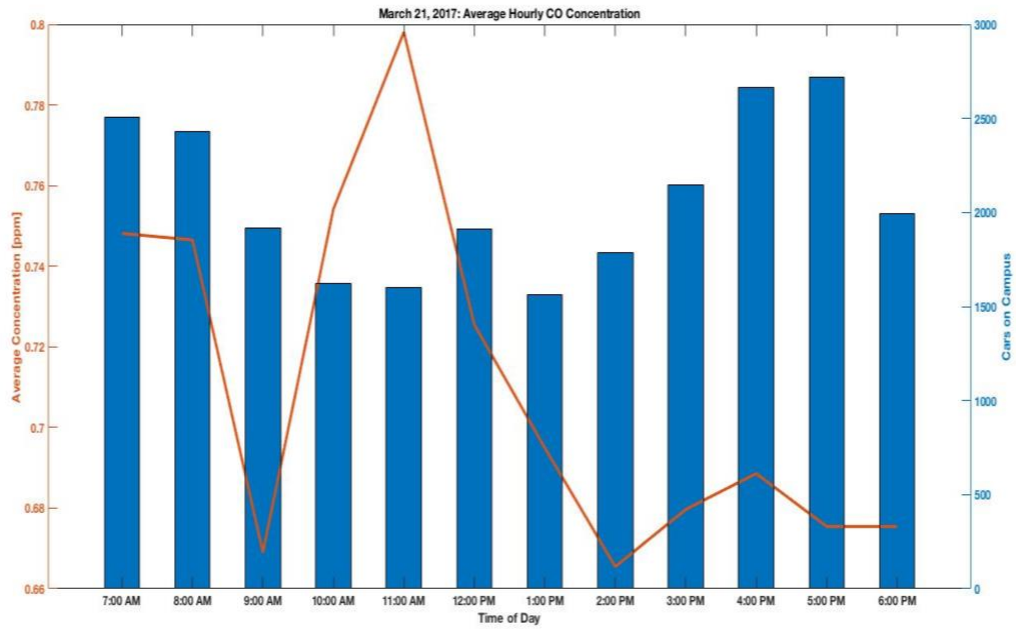


Figure 2.10: Average Hourly Carbon Monoxide Campus Levels for March 21, 2017

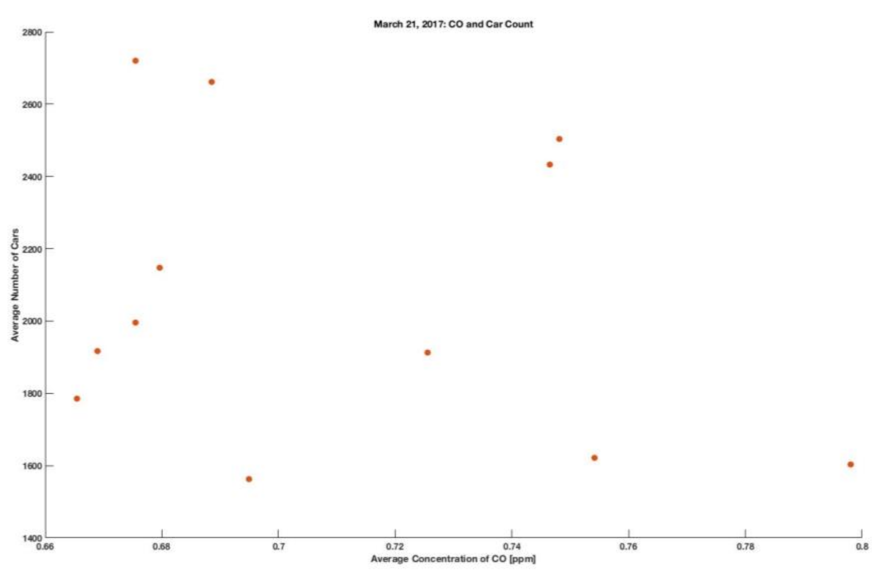


Figure 2.11: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for March 21, 2017

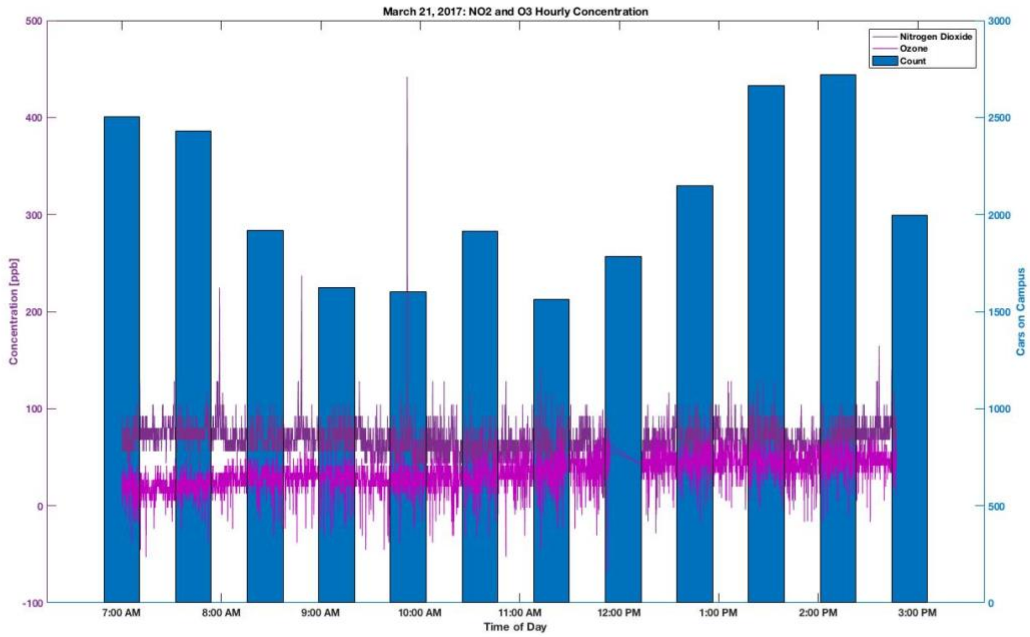


Figure 2.12: Hourly Nitrogen Dioxide and Ozone Campus Levels for March 21, 2017

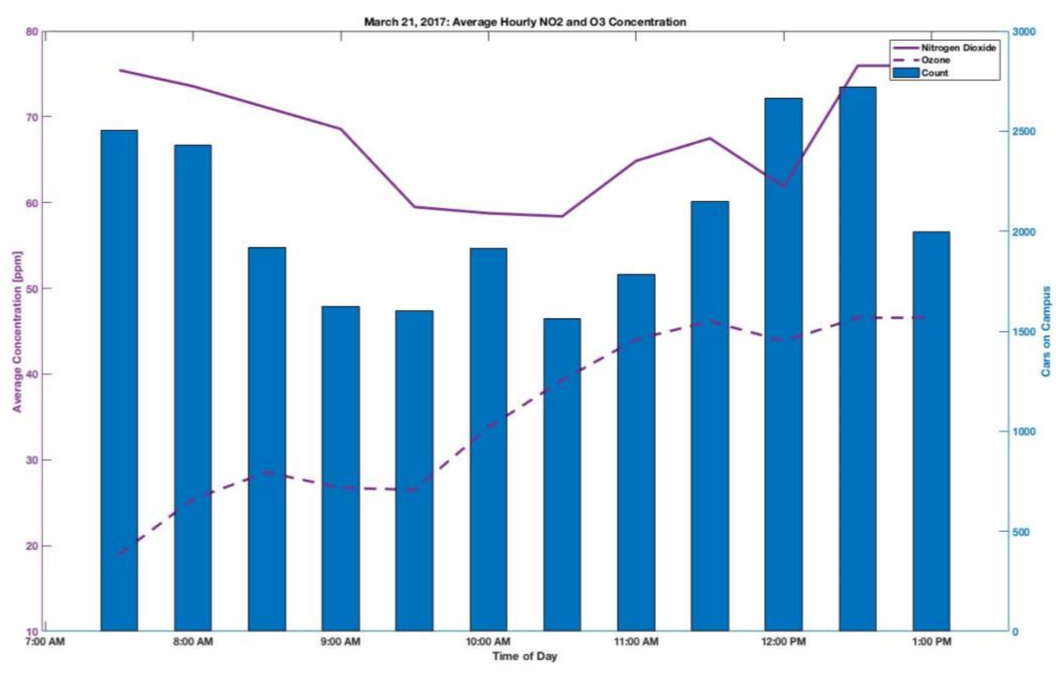


Figure 2.13: Average Hourly Nitrogen Dioxide and Ozone Campus Levels for March 21, 2017

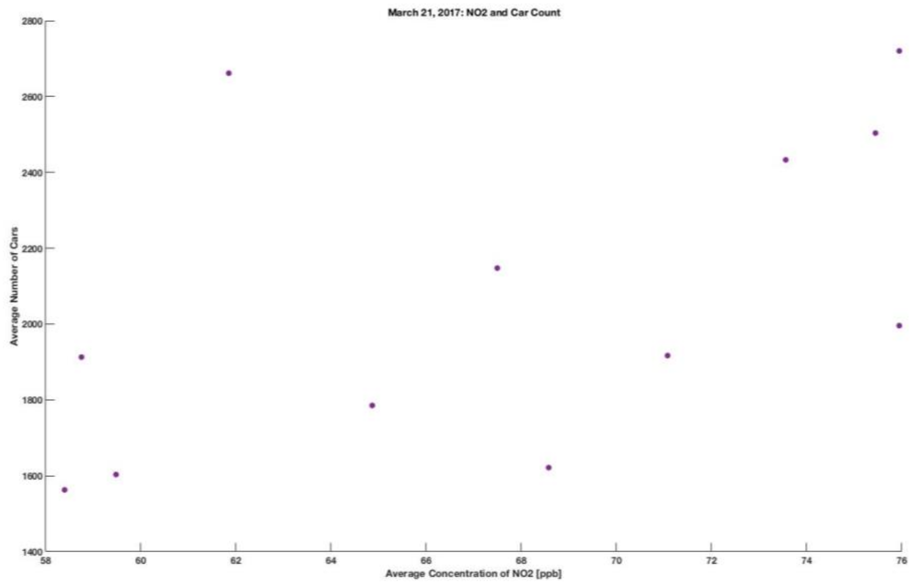


Figure 2.14: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for March 21, 2017

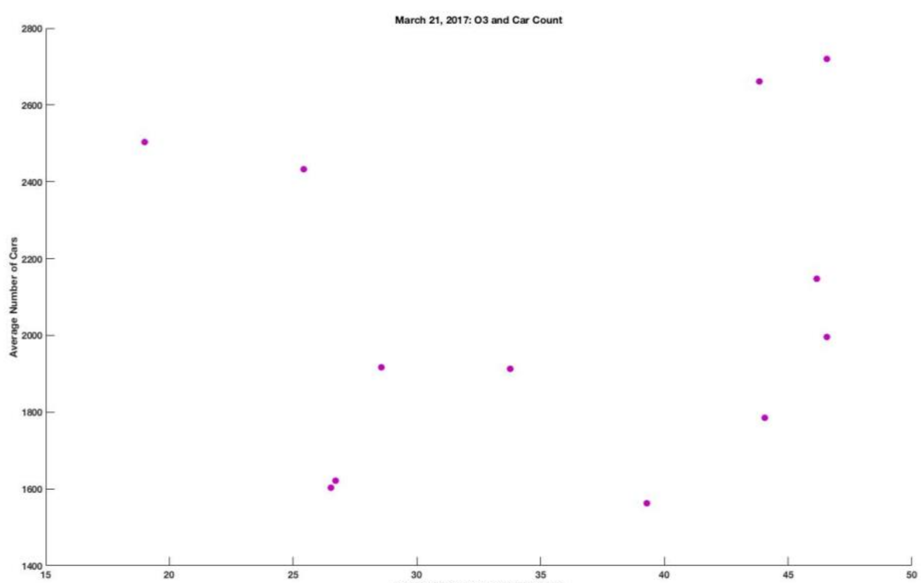


Figure 2.15: Average Hourly Ozone Concentration vs. Average Hourly Car Count for March 21, 2017

The hypothesis is that CO and NO_2 concentrations would follow the pattern of traffic flow. High counts would be expected to occur at 8:00 AM, 9:00 AM, around 12:00 PM, and 5:00 PM. These are typically rush hour times for campus, around 8:00 AM – 9:00 AM many professors, staff, and commuting students are driving in to campus for a day of work or classes. Around 12:00 PM there is a lunch-hour rush that can explain the high car count here. At 5:00 PM, most professors and staff typically head home for the day. These rush times are common knowledge among those who have worked or attended school at Ohio State, just by experiencing it on a daily basis. Since the car counts are coming from garage data, a higher count could indicate more congestion as drivers sit in the garages waiting their turn to exit or waiting at red lights. There could be significant idling time for these drivers that the CO and NO_2 concentrations increase as more is emitted into the air by tailpipes.

Looking at Figures 2.9 and 2.12 (and the corresponding ones in Appendix 4.2), the raw gas concentrations are too noisy to identify any possible associations among the concentrations and car counts. As for the very high gas concentration values in these figures, a possible explanation could be the presence of a nearby bus or truck, right behind or ahead of the bus carrying the sensors

To help identify the hypothesized patterns, the raw gas concentration values are averaged on an hourly basis and plotted with hourly car counts in Figures 2.10 and 2.13.These figures do show that some high values of average gas concentrations correspond to some high values of garage car counts, in general, and especially when considering the plots for the other days shown in Appendix 4,2, the correspondence between gas concentrations and car counts is not systematic.

In order to further analyze these data, the average concentrations of each pollutant are plotted against the car counts in the form of a scatter plot. These relationships are shown in Figures 2.11, 2.14 and 2.15 with CO, NO_2 , and O_3 concentrations respectively for March 21, 2017 (the corresponding plots for the other days are seen in Appendix 4.2). The purpose of these figures is to look further for any kind of patterns between the variables. However, these figures do not indicate any obvious patterns among them. As discussed previously, high concentrations of CO and NO_2 are expected to be associated with the higher car counts, but there are several points in these figures where a low concentration is associated with a high car count. This indicates that among these data, there is no obvious pattern and that there is a need for further data collection and analysis in the future.

Using ARCGIS, a map was created of campus and the sensor data was overlaid with the readings' corresponding GPS points for March 21, 2017. Higher concentrations of data were displayed by more red data points. This map is shown below in Figure 2.16.

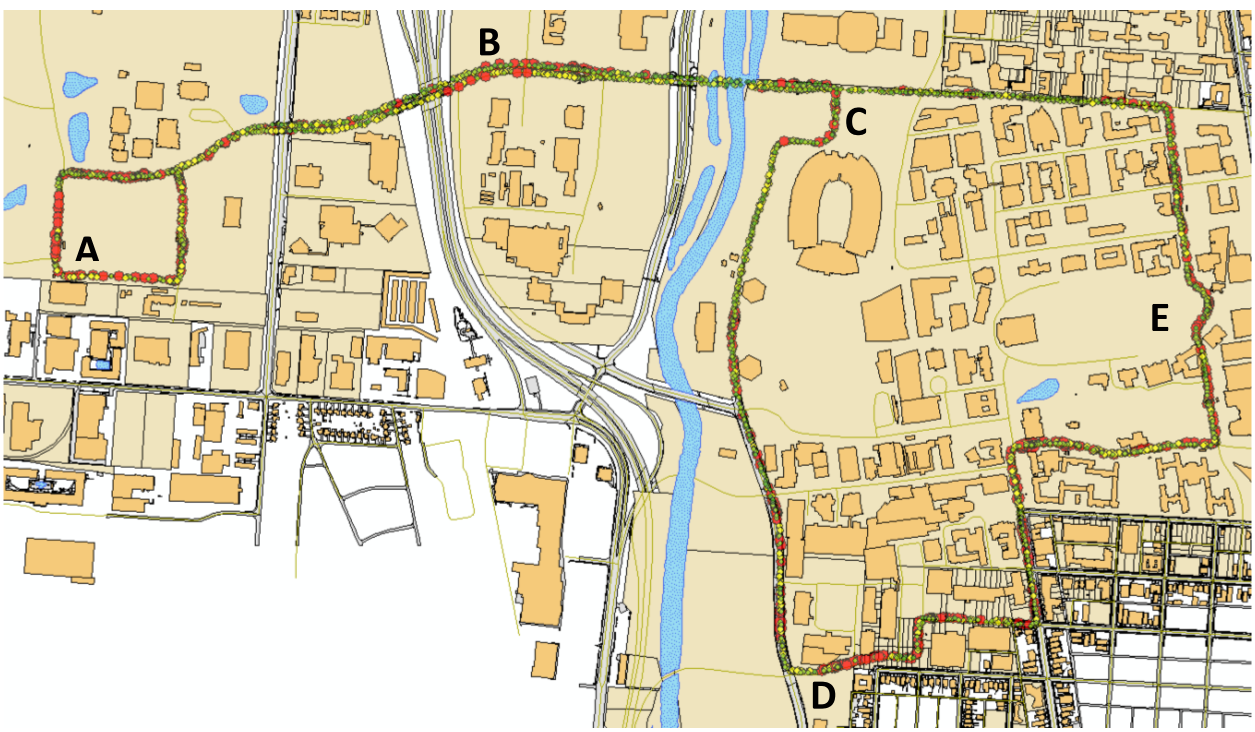


Figure 2.16: Sensor Data on Campus for March 21, 2017

Looking at this map, locations with a higher population of red data points include (A) the satellite surface parking lots, (B) Agricultural campus, (C) nearby the stadium surface parking lots, (D) medical campus, and (E) along College Road. These locations of high concentration are to be expected. All are areas of high traffic. Agricultural campus is located on a busy road, and is a bus stop location for several different CABS. In addition, the freeway is close by. Winds in Ohio are typically from the west and this could be affecting these high concentrations, as emissions could be blown in the direction of campus from the freeway. The parking lots are usually full of commuting students' vehicles. Medical campus attracts not only doctors and medical students, but patients and visitors as well. College Road is the main outer edge road on campus and is frequently traveled by both cars and buses. There are several parking garages located along this road as well. These are all plausible explanations for the high concentrations and the representative larger red data points on the map.

Conclusion

3.1 Contributions

Although CABS data collection was sporadic throughout the past year, the data that were provided gives lots of insight in to on campus air quality. The US EPA retains a 35 ppm standard for a 1-hour average for CO (Stephen), a 100 ppb 1-hour standard for NO_2, and a 70 ppb 8-hour standard for O_3. (United States Environmental Protection Agency, "National Emissions Inventory"). The CO emissions reported do not show numbers this high, however the NO_2 emissions reported by the sensors often reach above and beyond the 100 ppb requirement. It is important to consider that these sensors will produce some range of error in their readings, but even so, anyone walking along these high concentrated locations is exposed and actively breathing in various emissions.

These data can contribute to potential urban planning of campus, if there is known locations with high level emissions, this could impact decisions such as parking lot/garage placement, landscape choices, potentially even class schedules and locations. However, the main takeaway from these data is motivation to learn more about traffic emissions. As the number of sensors on the buses increases, and the more data that can be post-processed, the more we can understand the air pollutants on campus. If there are locations with high level emissions, perhaps planting more trees around that area could help with carbon reduction. The university has already made steps forward in reducing the carbon footprint by switching many of the diesel-powered CABS buses to CNG-powered buses. The addition of these data from the bus sensors could contribute to more green initiatives and improved public awareness.

3.2 Additional Application

While on campus emissions are not constantly surpassing US EPA limits, long term exposure to these gases have been linked to health problems later in life. The average student at Ohio State attends the university for about 4 years and walks to classes 5 days per week. The average class walk takes approximately 15 minutes from housing to classroom, inferring that every student on campus is subjected to at least 30 minutes of exposure per day or 2.5 hours per week. Exposure to O_3 has been connected to reduction in Forced Expiratory Volume (FEV) testing in both children and adults (Langstaff), weaker lungs can lead to lung infections or potential development of asthma. It can also harm lung tissue and inflame airways. Much less severe, but still harmful effects of O_3 exposure include shortness of breath, sore throat, and cough (United States Environmental Protection Agency, “Health Effects of Ozone Pollution”).

CO exposure has been linked to “…cardiovascular disease such as congestive heart failure, arrhythmia, and non-specific cardiovascular disease” (Stephen). It was noted that low level exposure of CO can increase the risk of these diseases. People with preexisting health conditions such as asthma, anemia, or diabetes could be susceptible to CO exposure effects given the nature of their preexisting conditions (Stephen). High concentrations of NO_2 can also lead to lung irritations, infections, or the development of asthma. Infection and asthma is a more increased risk when the exposure is long term (United States Environmental Protection Agency, “Basic Information about NO2”).

3.3 Future Work

Future work on the project should include analysis of CABS sensor data over longer periods of time so that there is a greater chance of repeatability and that seasonal analysis can occur. The sensor data plots for the project, as seen in the Appendix 4.2, for April and May make the overall data set look inconsistent if you compare all days. However upon comparison of all March data, and all May data, there are much more evident consistencies among sensor readings. More consistent data collection would help to support the hypothesis with less inferences.

The new sensing units will be deployed on to the CNG CABS buses this month, limitations with attaching them earlier in the year included scheduling usage of the Engineering Department’s laser cutter, and complications with the CFD analysis software. In addition to more frequent data, further analysis should be done regarding on-campus traffic. The CampusParc data included location, but for the scale of this project, is only utilized as a general, campus-wide traffic proxy.

As previously stated, it does not account for surface parking lot traffic. Plotting the car data by location on to a campus map, categorizing by the number of car transactions by garage would provide a more accurate analysis. Mapping both garage data and CABS sensor data by hour could provide even more detail of the correlation between campus traffic and campus traffic emissions.

3.4 Summary

This investigation and analysis created a method of regular low-cost mobile air quality sampling for OSU's campus utilizing CABS as the mobile platform. These sensors located highly concentrated areas of traffic emissions. This was done by building and coding air quality sensors, constructing a housing unit for the sensors, utilizing CampusParc garage transaction data for a campus traffic proxy, then comparing the sensor readings with the number of cars on campus during that time. It was initially expected that CO would follow the campus traffic flows. After data analysis, these methods did not yield results as expected. NO_2 concentrations seemed to be the pollutant that most followed the traffic data patterns out of the three. It is important to note that the sensors will produce some error in readings. Locations of high concentration included the locations of large surface parking lots, CABS bus stops, and highly populated campus areas. As winds in Columbus are typically from the west, the OH-315 freeway that runs north to south is west of campus and winds could be transporting freeway traffic emissions towards campus. These elevated emission levels can contribute lots of spatial information to the university, and could potentially assist decision making in regards to class scheduling, urban planning, and landscaping if further data collection and analysis is pursued. It is possible that students who are breathing in this air on a daily basis could experience health effects due to long term low level exposure. It is important for the university faculty, staff, and students to be aware of air quality data as it affects them on a daily basis and cannot be avoided. Understanding where and why there are high concentration level locations on campus may help pedestrians make an informed decision on their walking routes, provide suggestions on where the best location is for studying outside or playing a sports game on campus greenspaces with friends, and could even help the university make steps forward in to further reducing their environmental impact. The potential health risks associated with air pollution exposure can motivate for opportunity for additional and further research and analysis of campus air quality.

Appendix

This Appendix contains sample data sets and plots of sensor data for the days indicated in the caption. Appendix 4.1 contains tables with example data from CampusParc and the sensors. CABS bus data. Appendix 4.2 contains sensor emission plots of raw sensor data, average hourly sensor data, and the average hourly sensor data vs. car count acquired from CampusParc garage data. Collection dates are noted below figures.

4.1 Tables

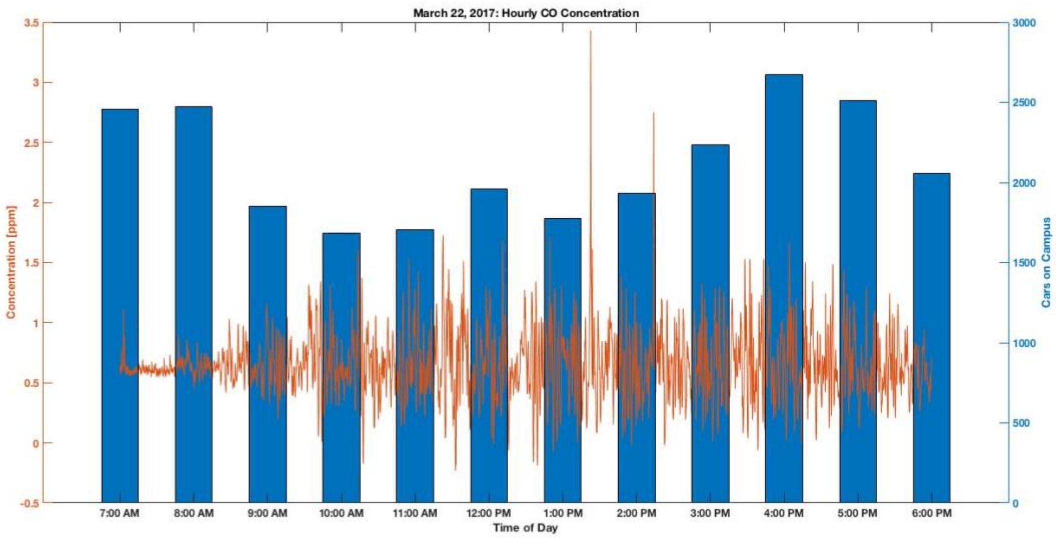
Table 4.1: Example CampusParc Garage Data

Garage	Garage ID	Date	Time
Lane Ave	15_EAC146 - Lane Ave R15 Exit C	4/18/17	8:08
Lane Ave	15_EAC146 - Lane Ave R15 Exit C	3/28/17	12:50
9th Ave E	13_EAC248 - 9th East R13 Exit EN	5/14/17	11:10
Ohio Union S	EAC142__27	4/9/17	7:41
Safe Auto	EAC247__00	4/29/17	5:23
Lane Ave	15_EAC146 - Lane Ave R15 Exit C	4/6/17	11:07

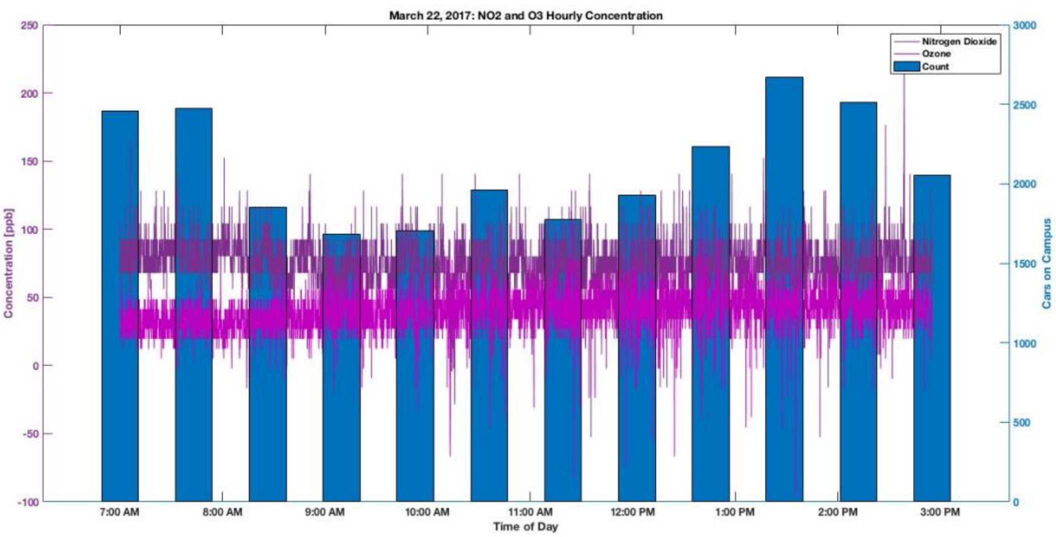
Table 4.2: Example Sensor Data

Timestamp	CO(ppm)	Nox Ozone(ppm)	Nox(ppm)
22/09/2016 10:29:00	149	129	67
22/09/2016 10:29:03	149	129	67
22/09/2016 10:29:06	147	125	63
22/09/2016 10:29:09	145	124	65
22/09/2016 10:29:12	145	120	62
22/09/2016 10:29:15	145	122	59
22/09/2016 10:29:18	144	119	56

4.2 Figures

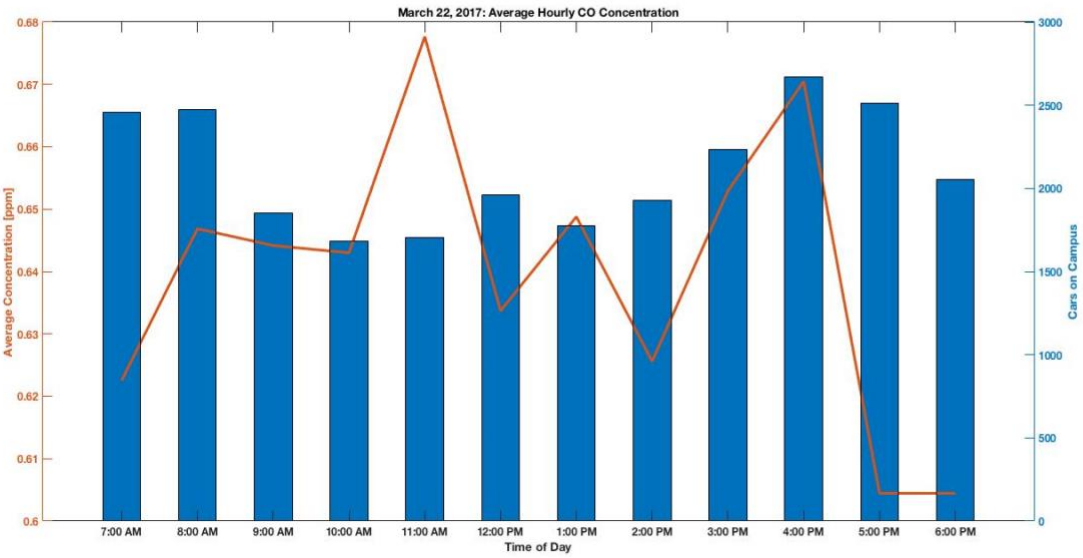


(a)



(b)

Figure 4.1: Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for March 22, 2017



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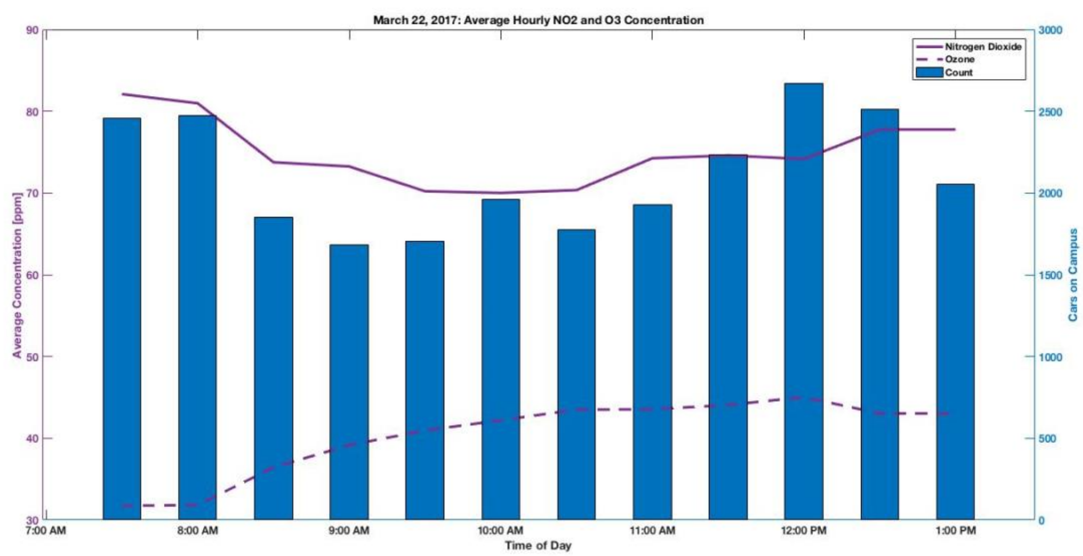

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Figure 4.2: Average Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for March 22, 2017

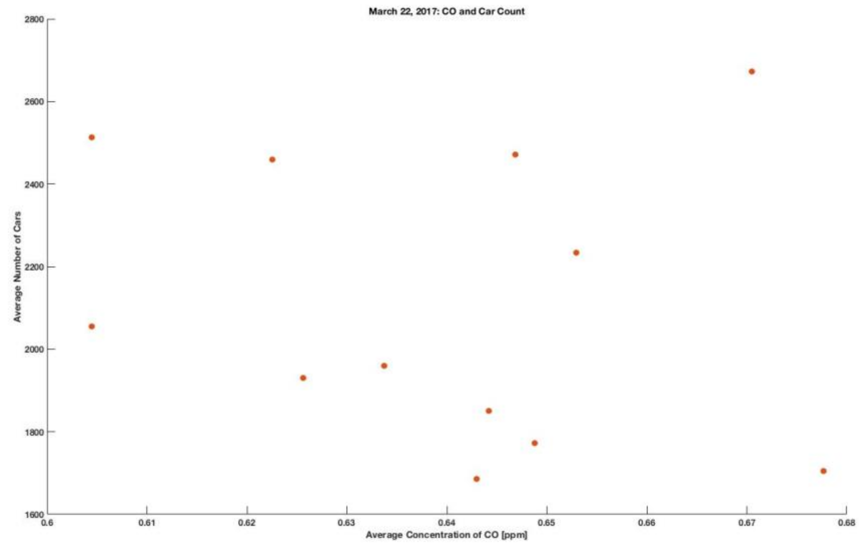


Figure 4.3: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for March 22, 2017

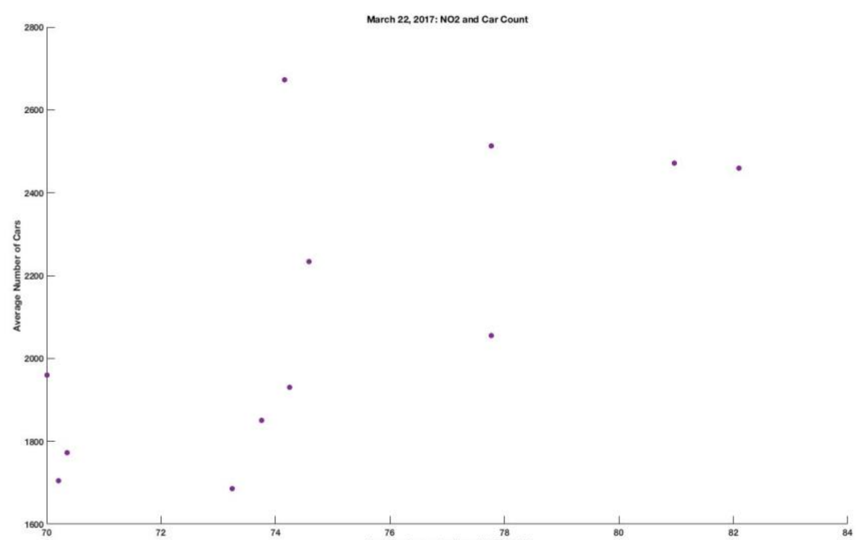


Figure 4.4: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for March 22, 2017

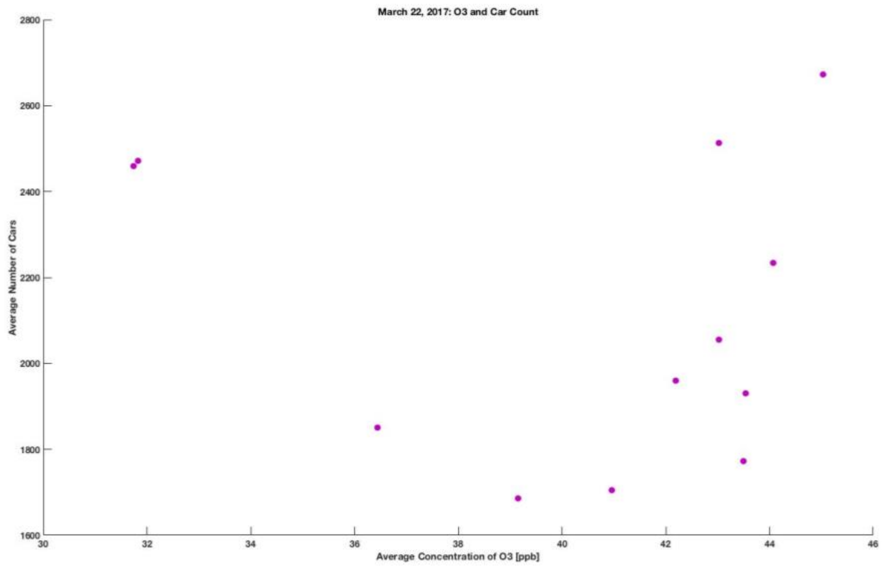
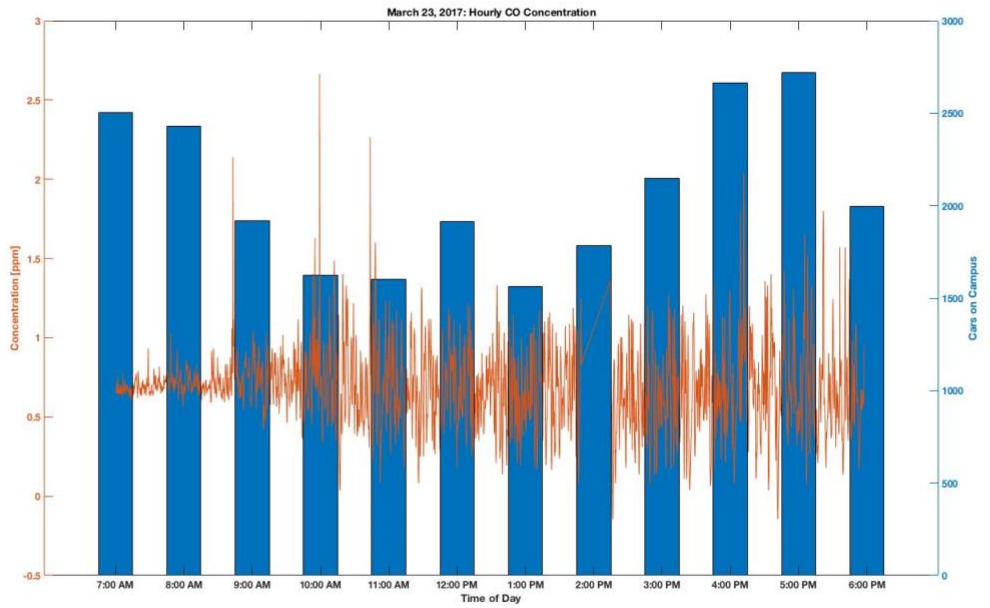


Figure 4.5: Average Hourly Ozone Concentration vs. Average Hourly Car Count for March 22, 2017



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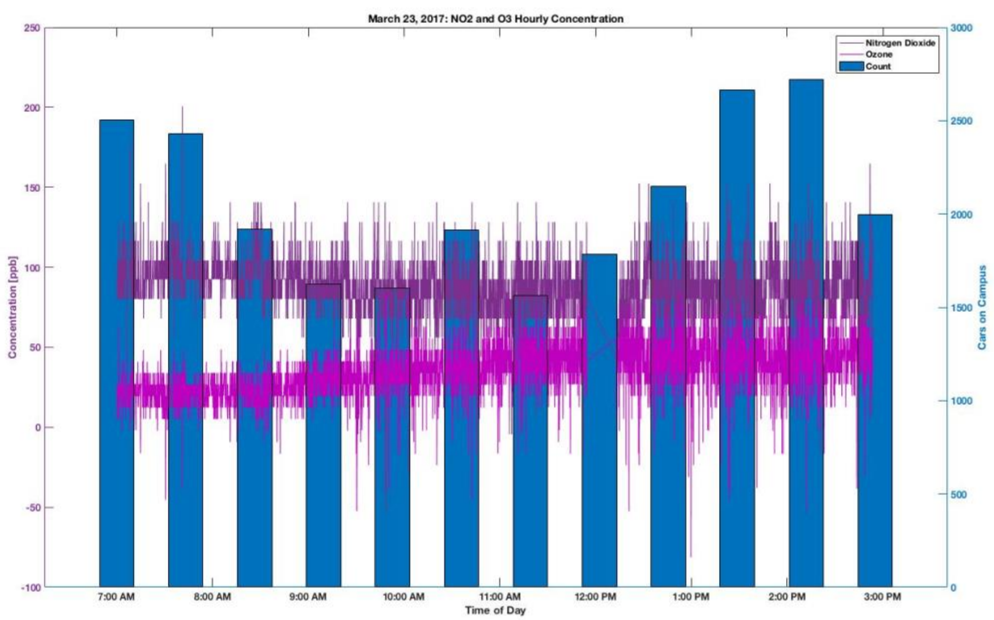

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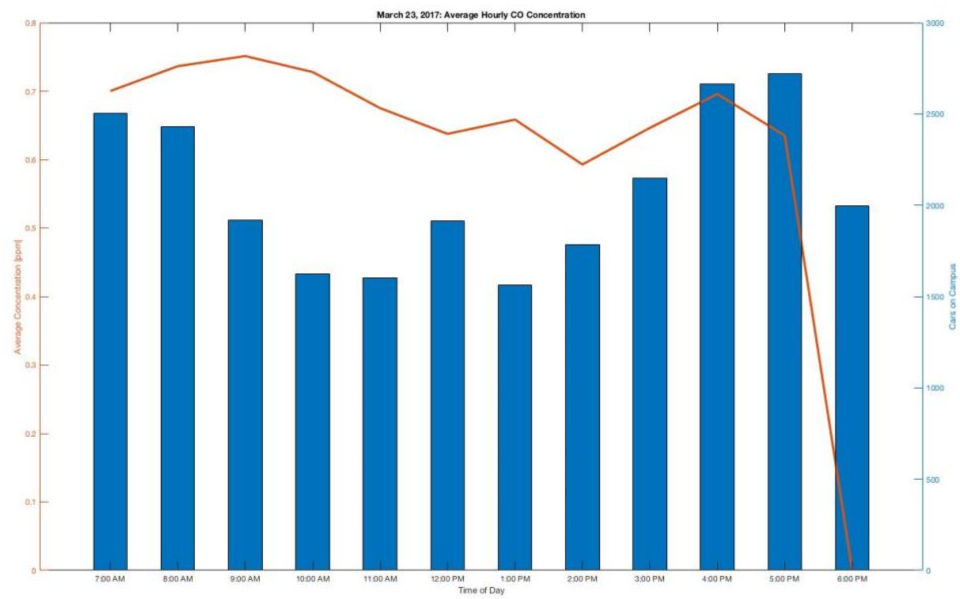
Figure 4.6: Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for March 23, 2017



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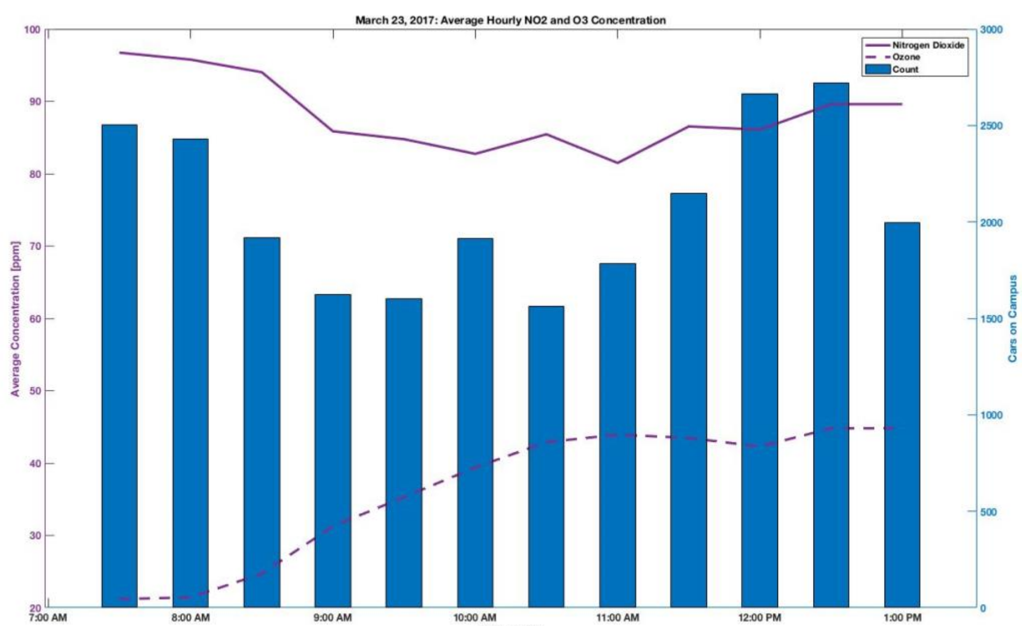

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Figure 4.7: Average Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for March 23, 2017

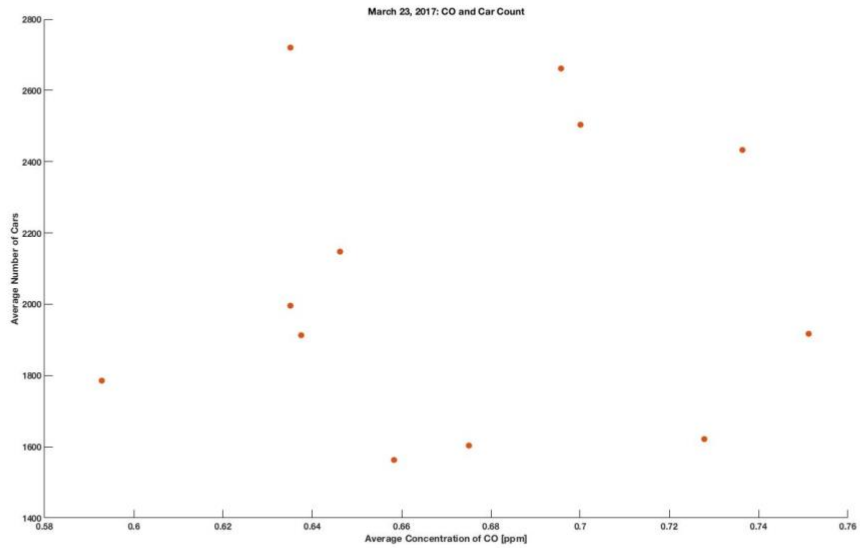


Figure 4.8: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for March 23, 2017

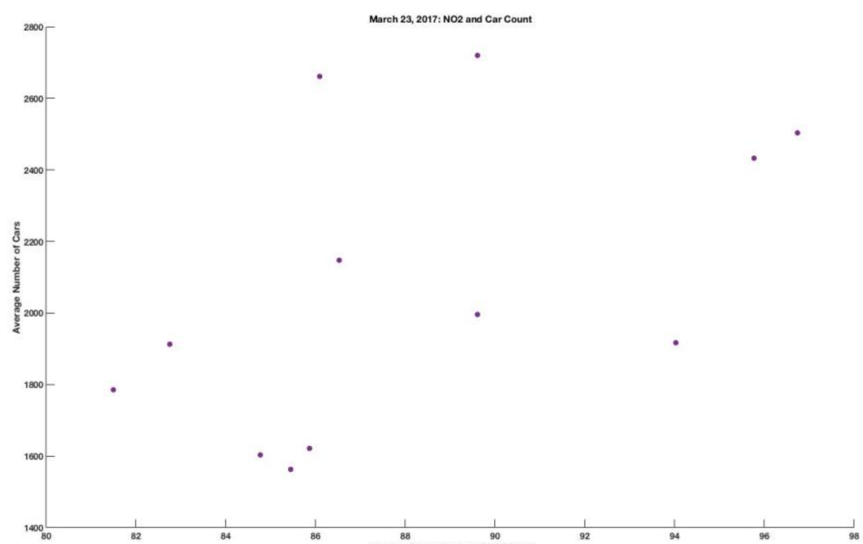


Figure 4.9: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for March 23, 2017

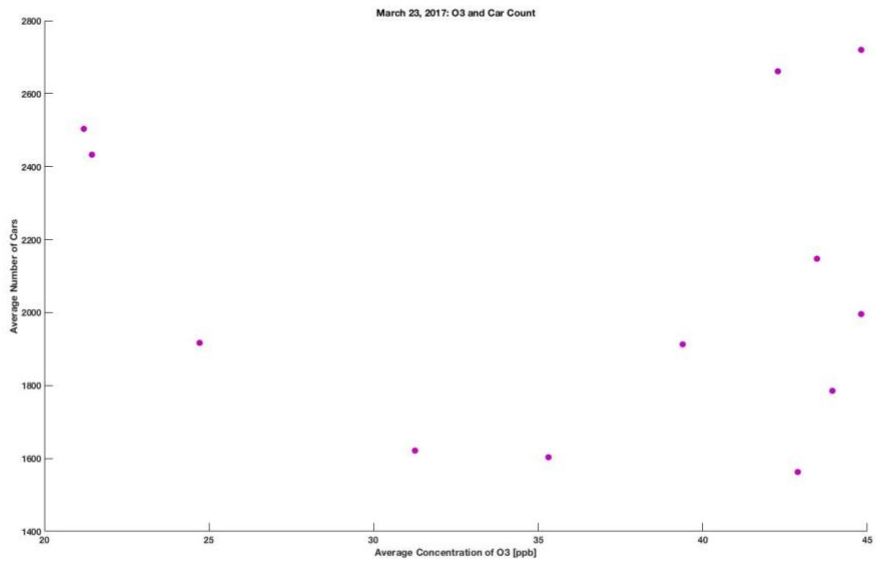
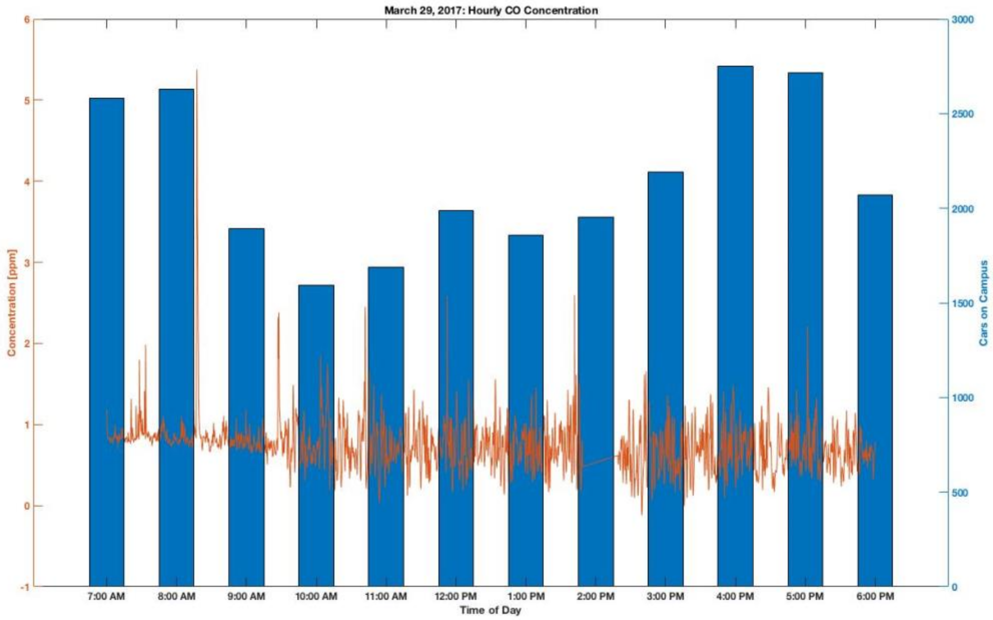


Figure 4.10: Average Hourly Ozone Concentration vs. Average Hourly Car Count for March 23, 2017



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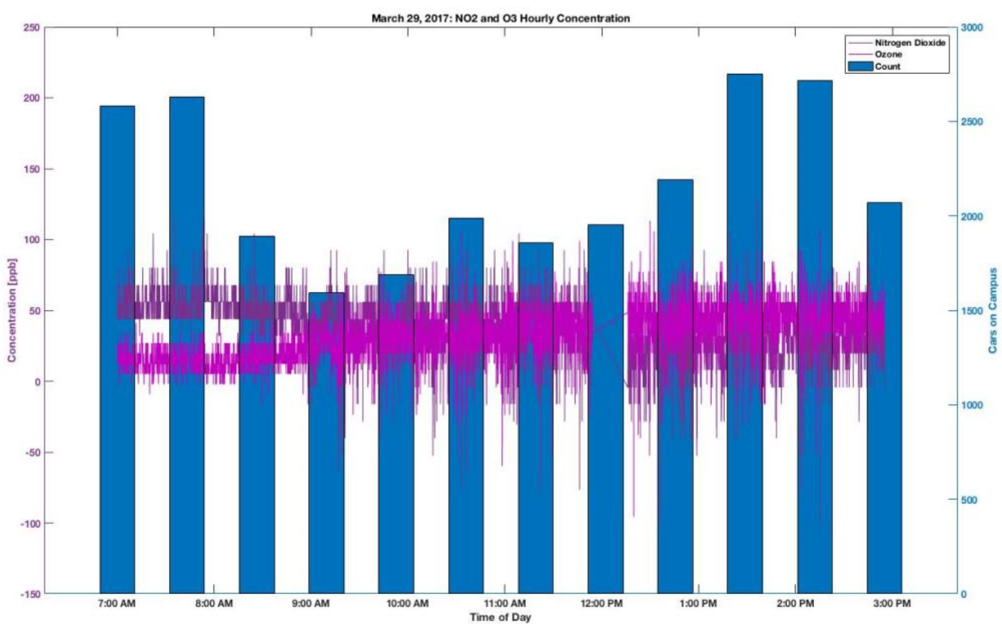

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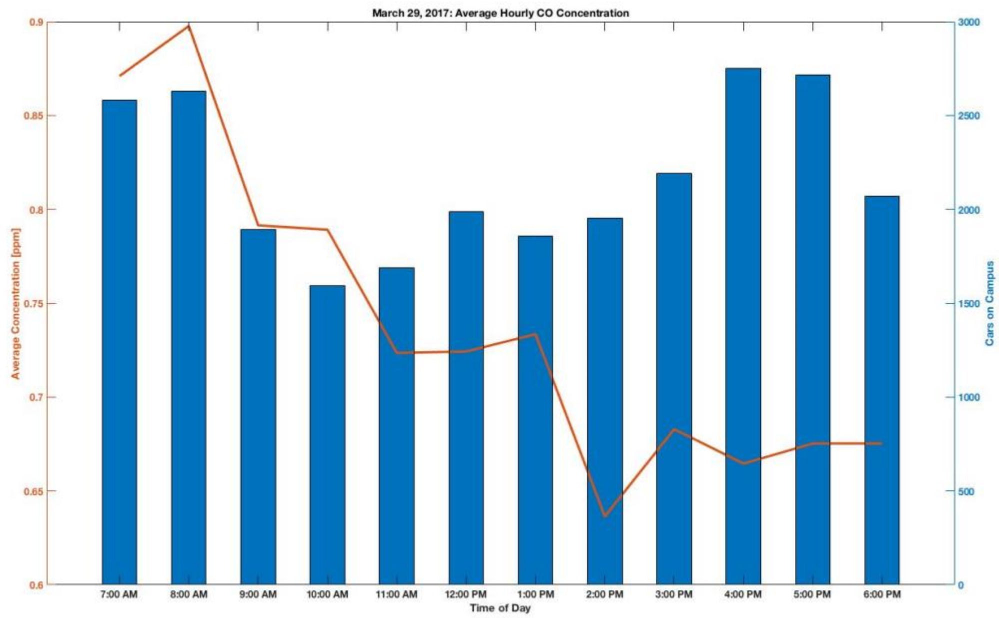
Figure 4.11: Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for March 29, 2017



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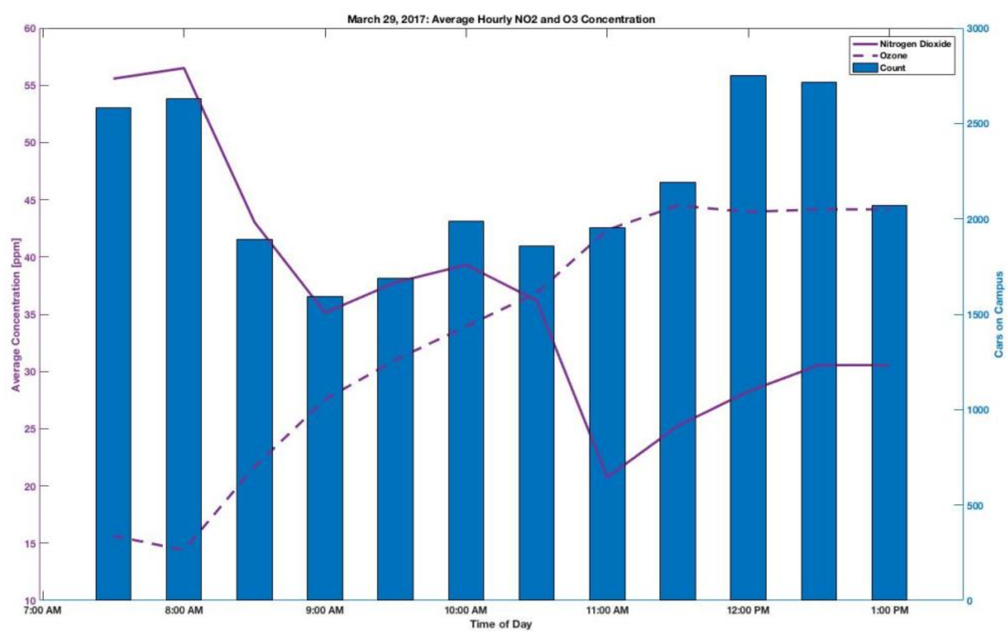

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Figure 4.12: Average Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for March 29, 2017

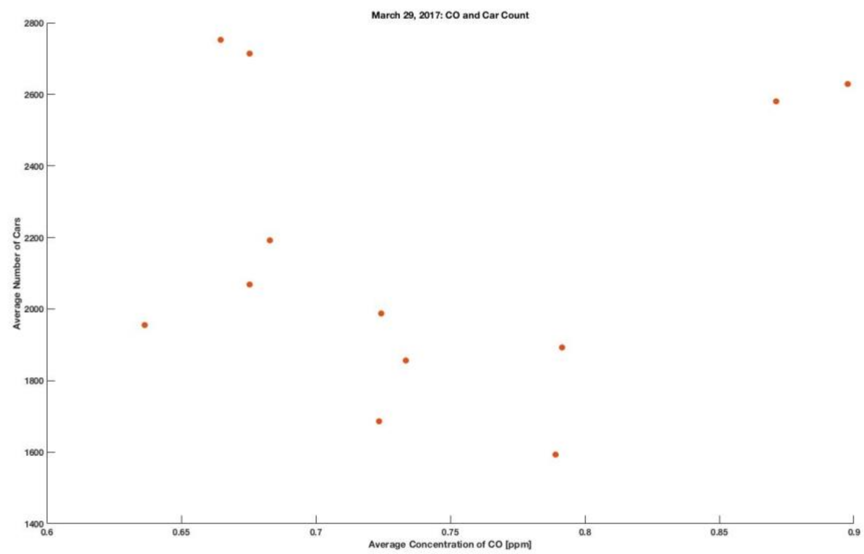


Figure 4.13: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for March 29, 2017

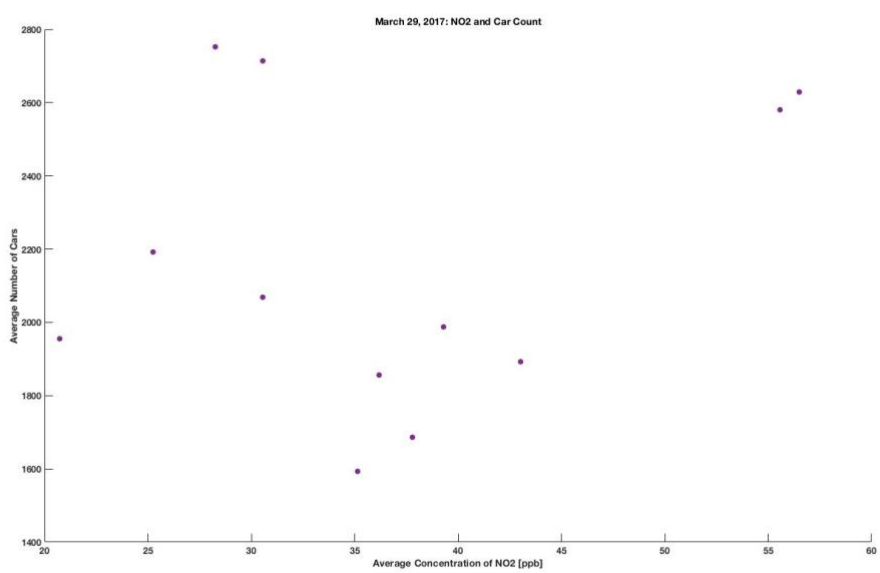


Figure 4.14: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for March 29, 2017

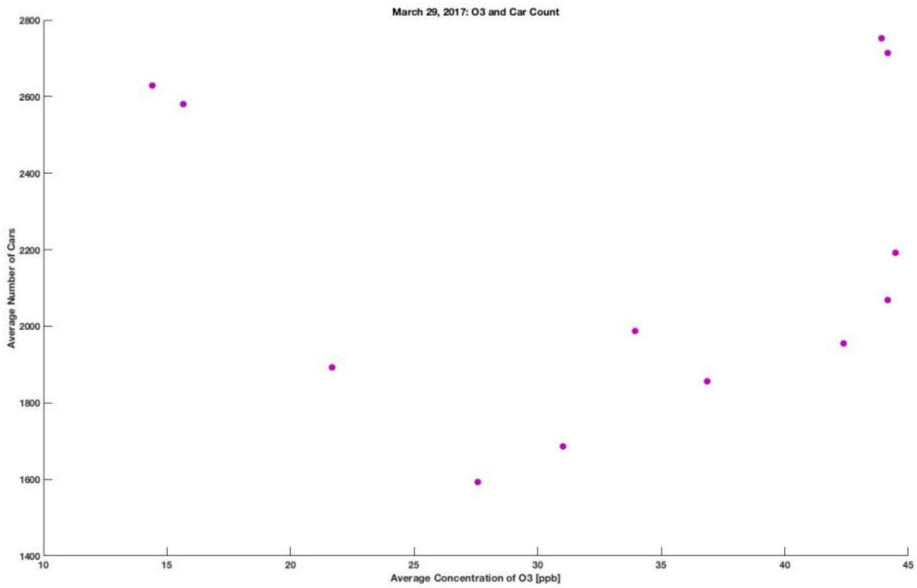
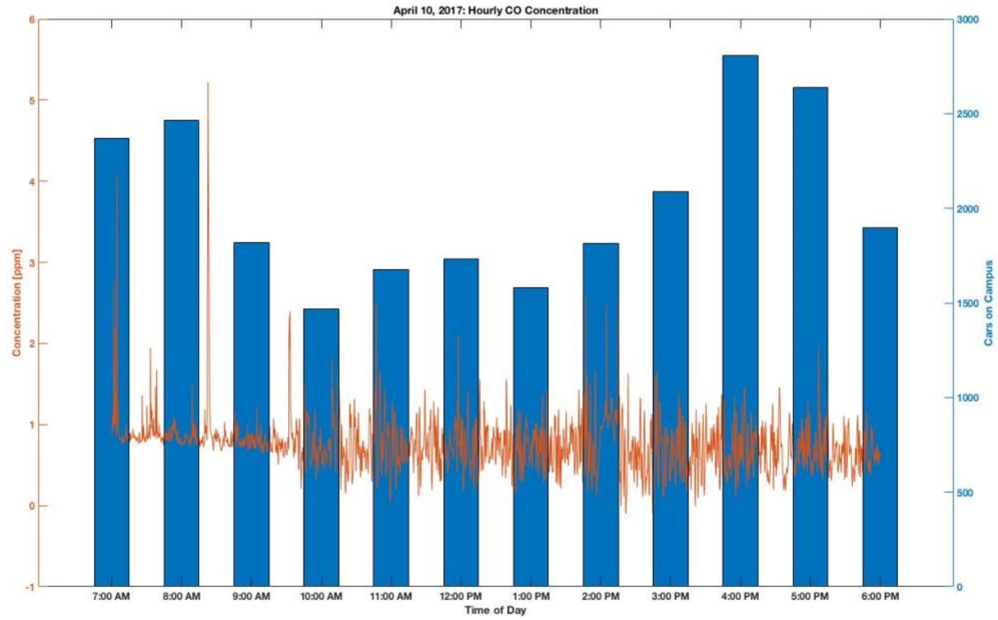


Figure 4.15: Average Hourly Ozone Concentration vs. Average Hourly Car Count for March 23, 2017



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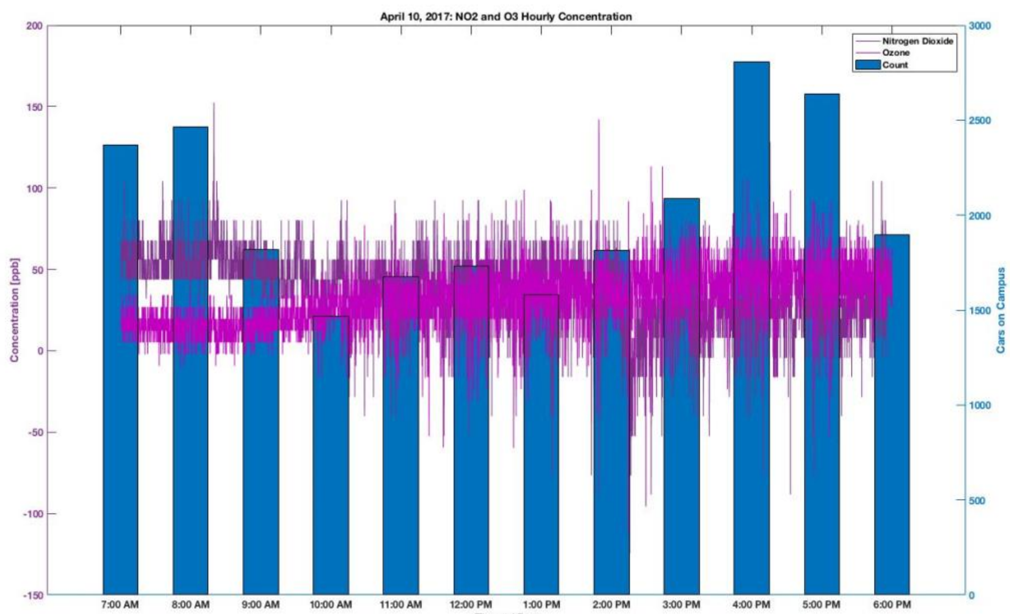

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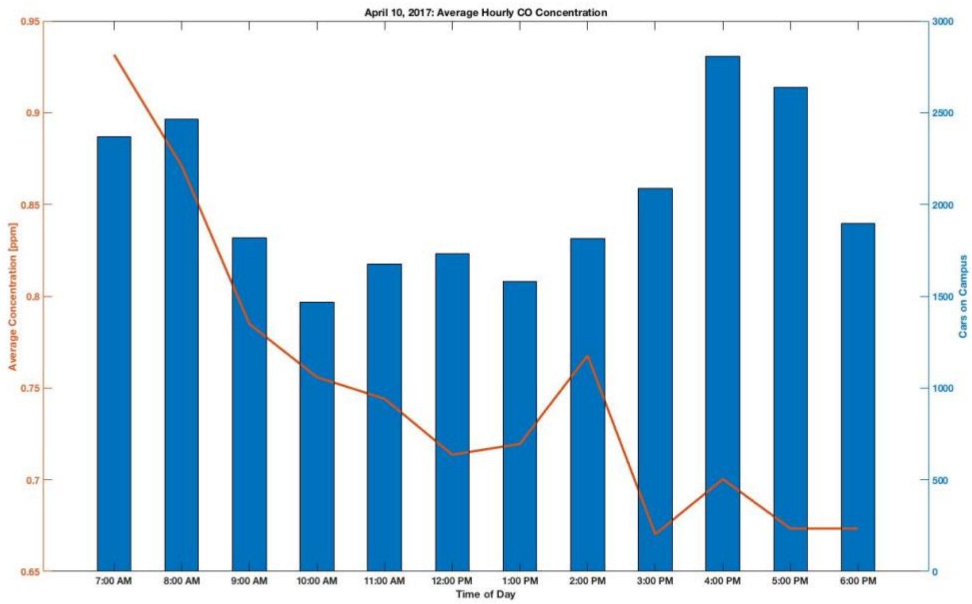
Figure 4.16: Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for April 10, 2017



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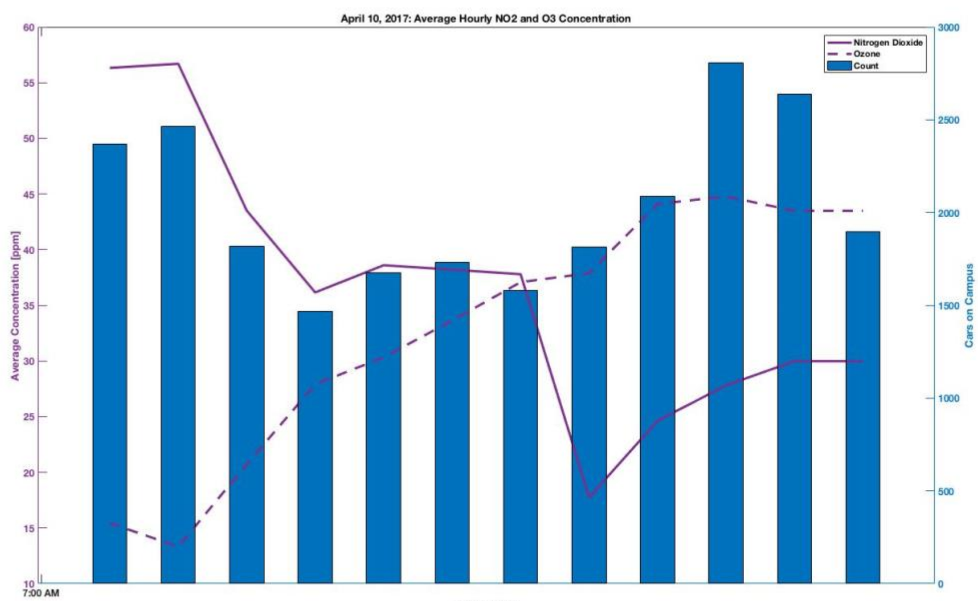

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Figure 4.17: Average Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for April 10, 2017

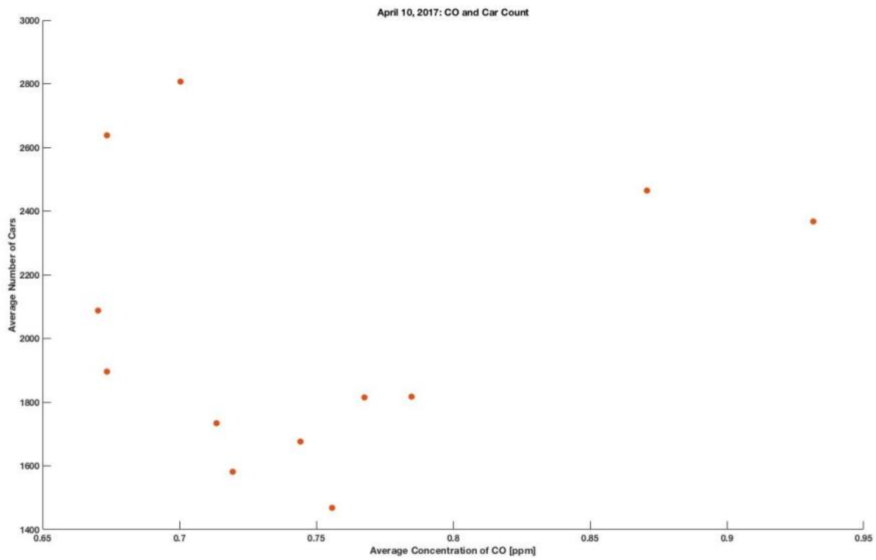


Figure 4.18: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for April 10, 2017

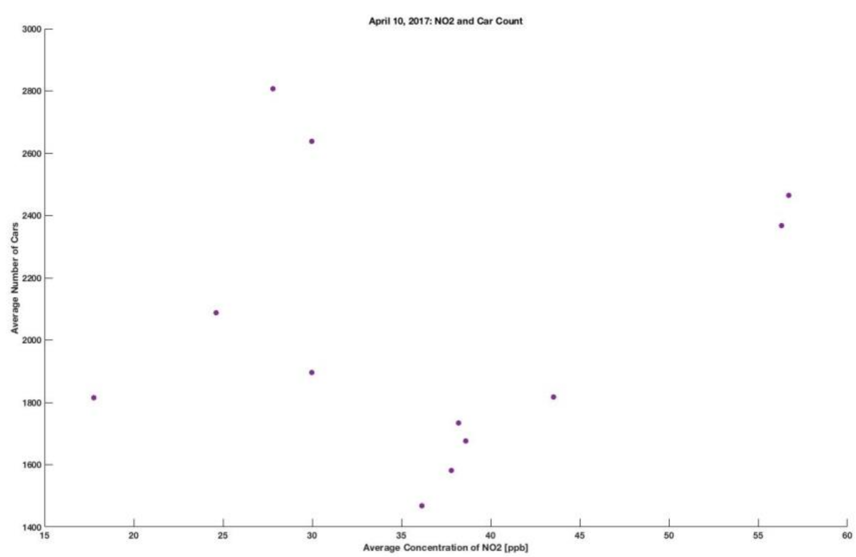


Figure 4.19: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for April 10, 2017

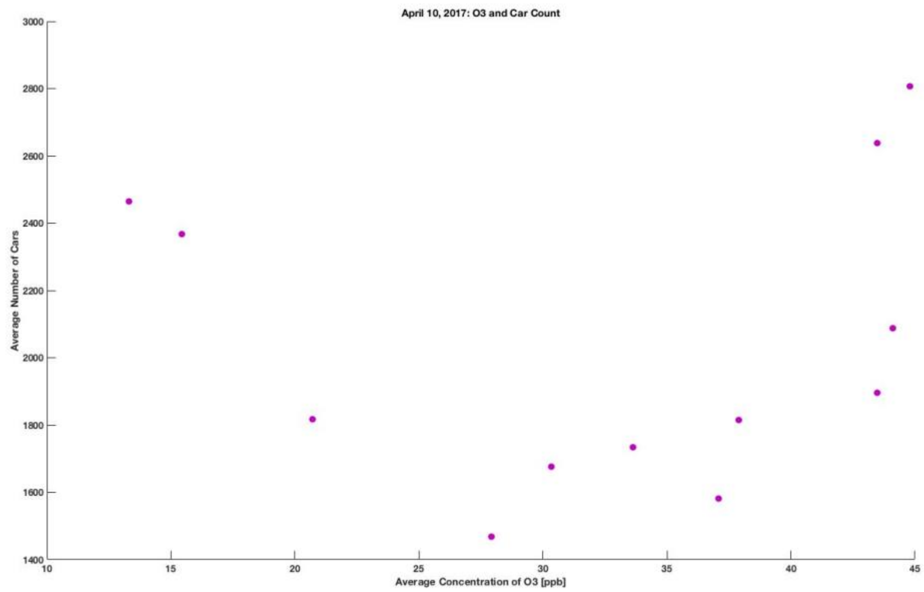
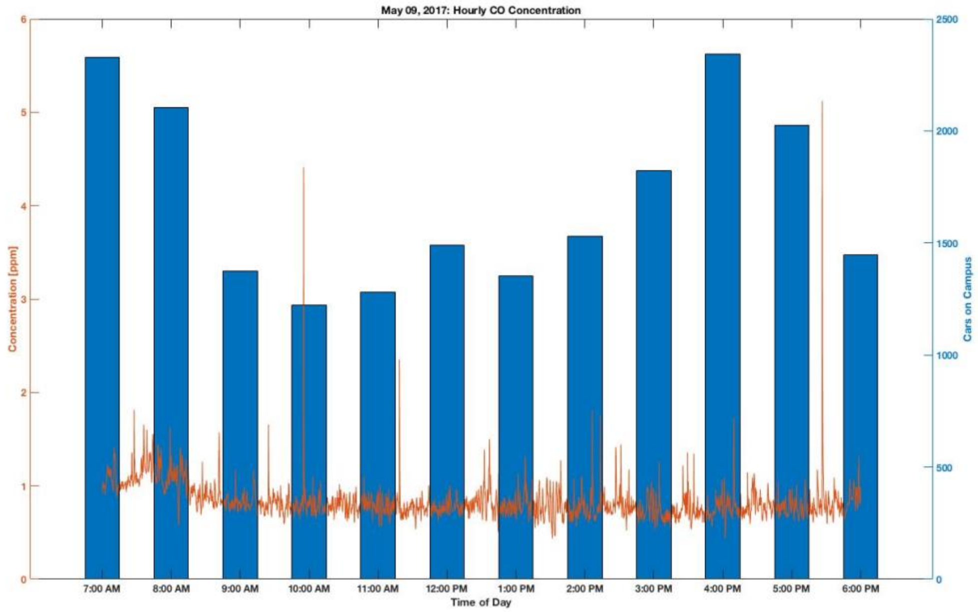


Figure 4.20: Average Hourly Ozone Concentration vs. Average Hourly Car Count for April 10, 2017



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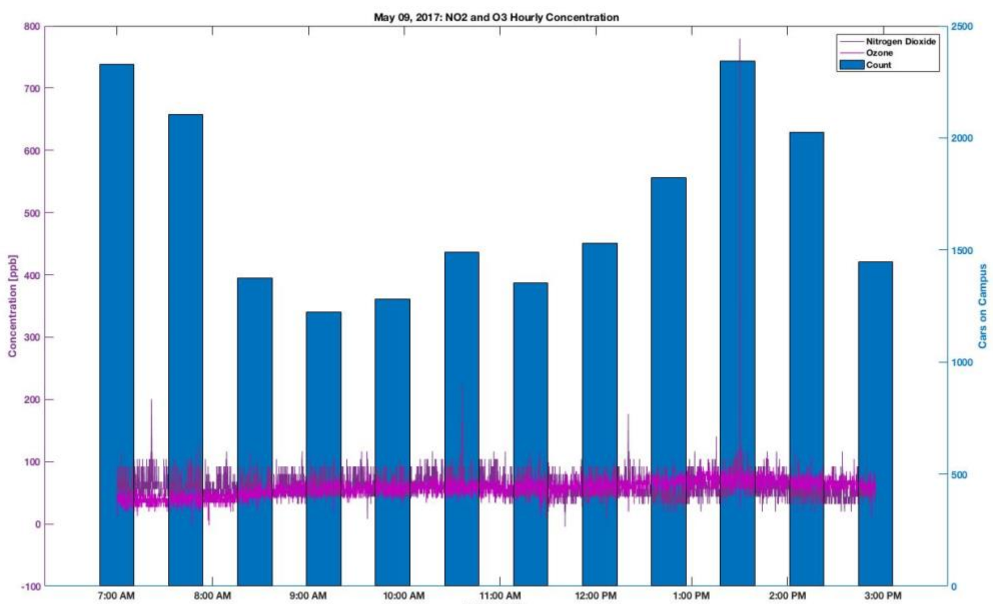

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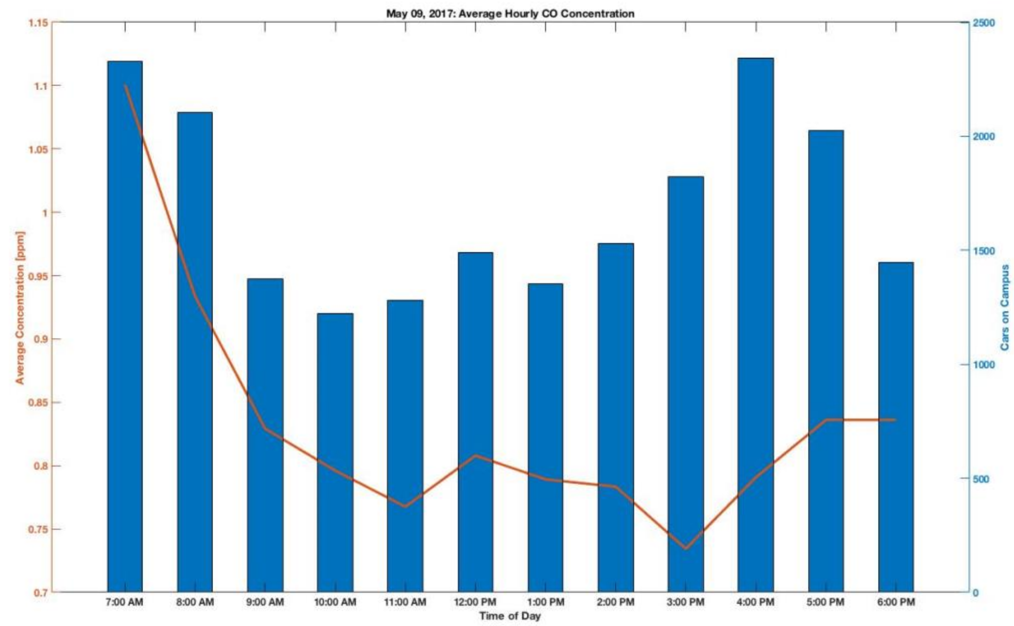
Figure 4.21: Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for May 09, 2017



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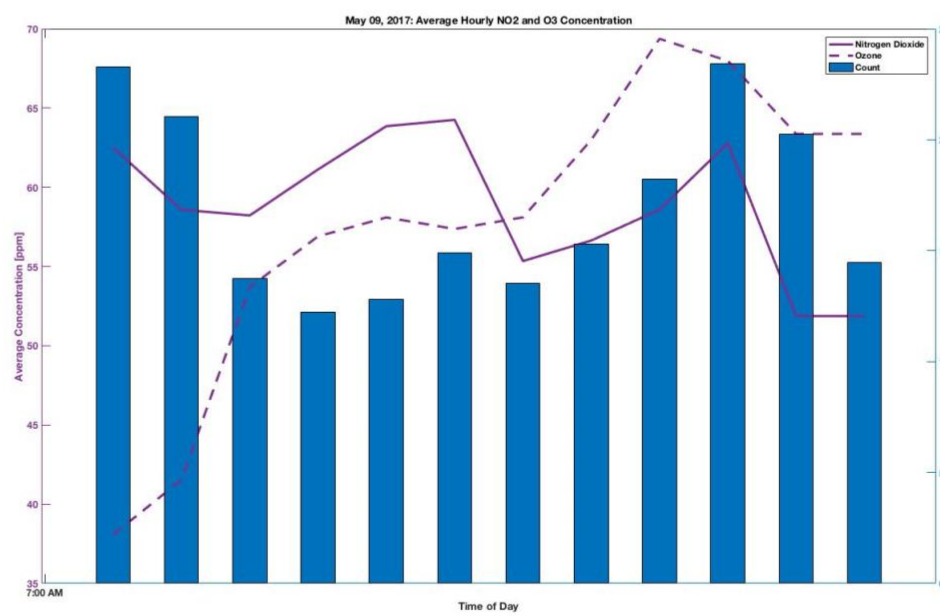

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Figure 4.22: Average Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for May 09, 2017

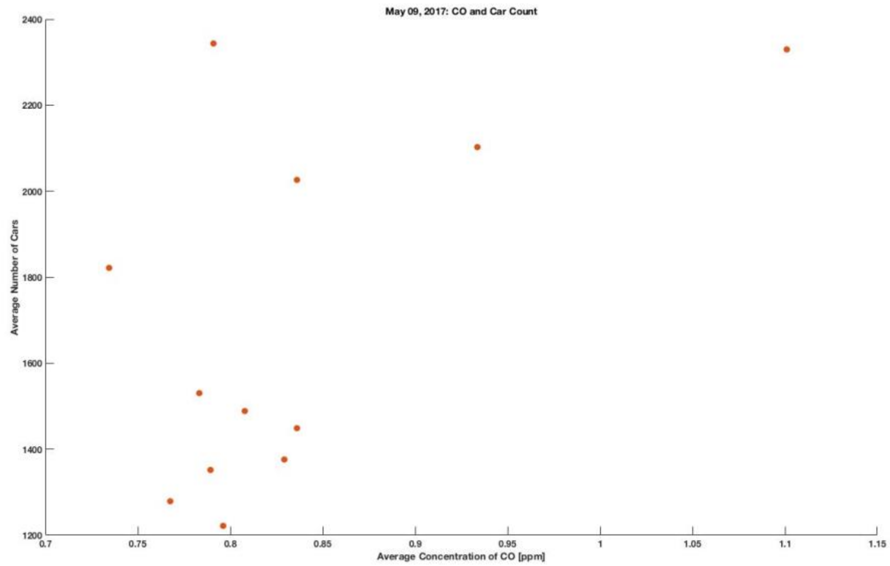


Figure 4.23: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for May 9, 2017

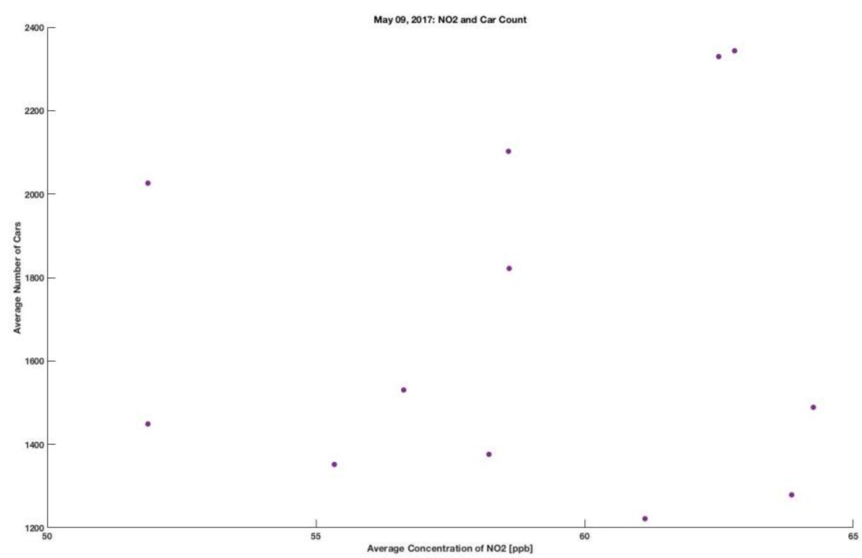


Figure 4.24: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for May 9, 2017

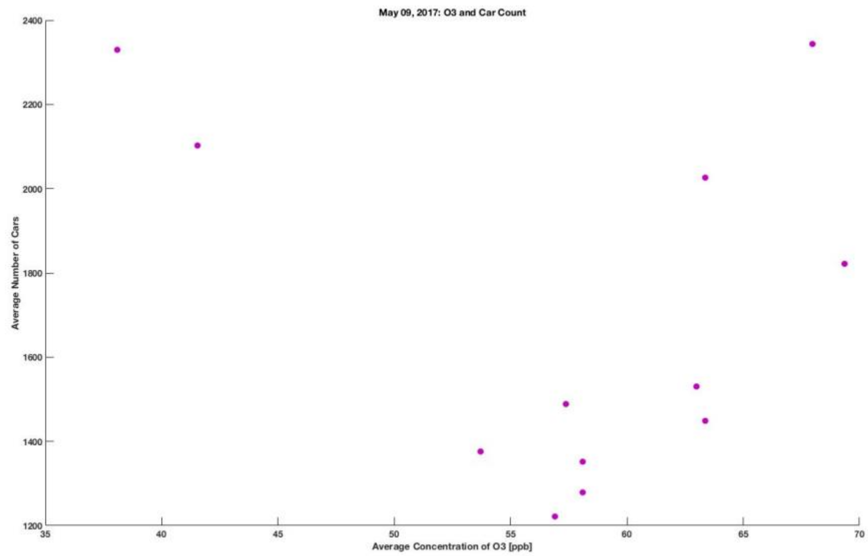
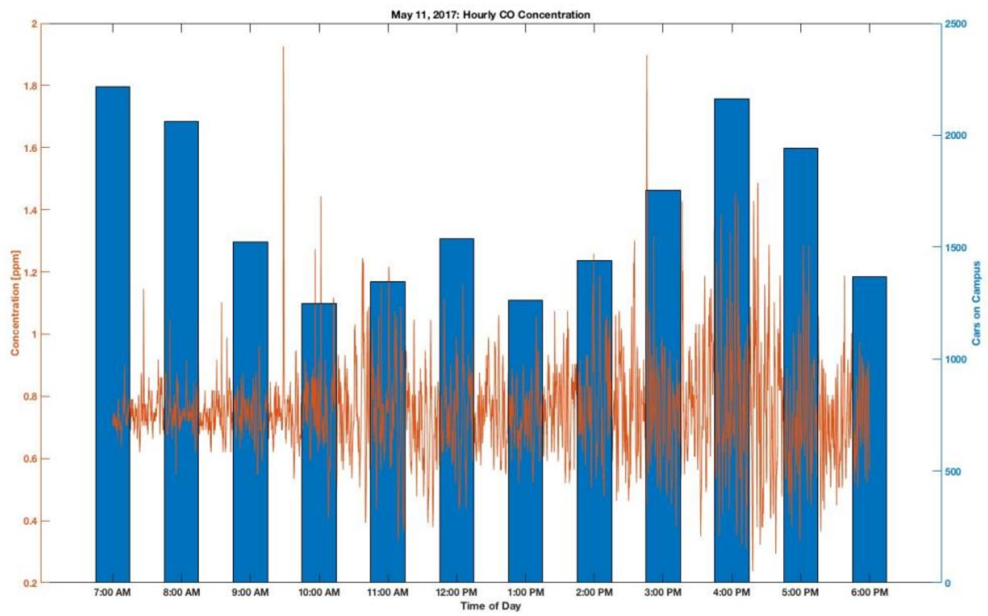


Figure 4.25: Average Hourly Ozone Concentration vs. Average Hourly Car Count for May 9, 2017



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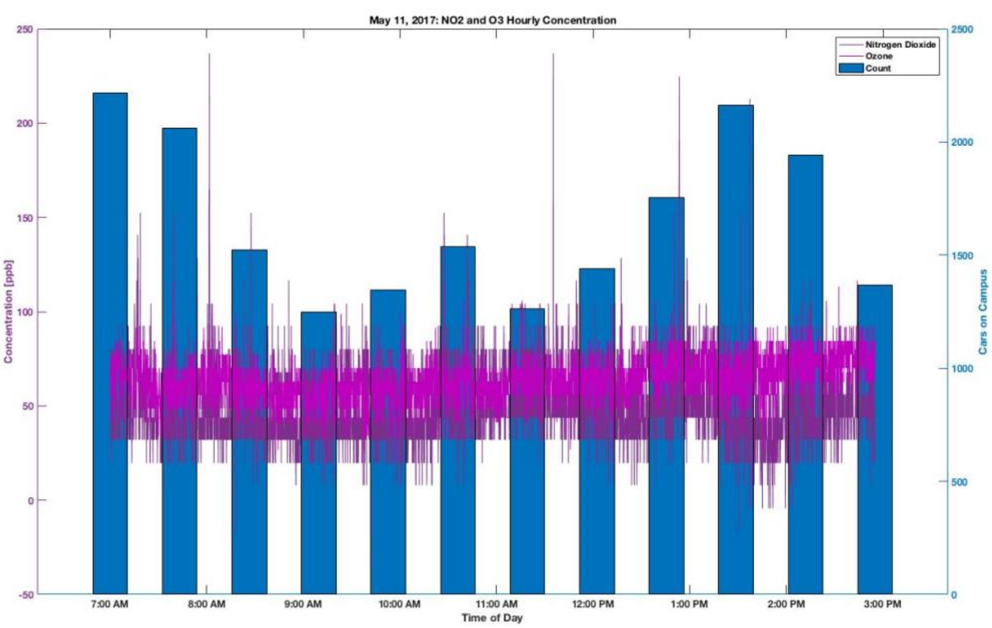
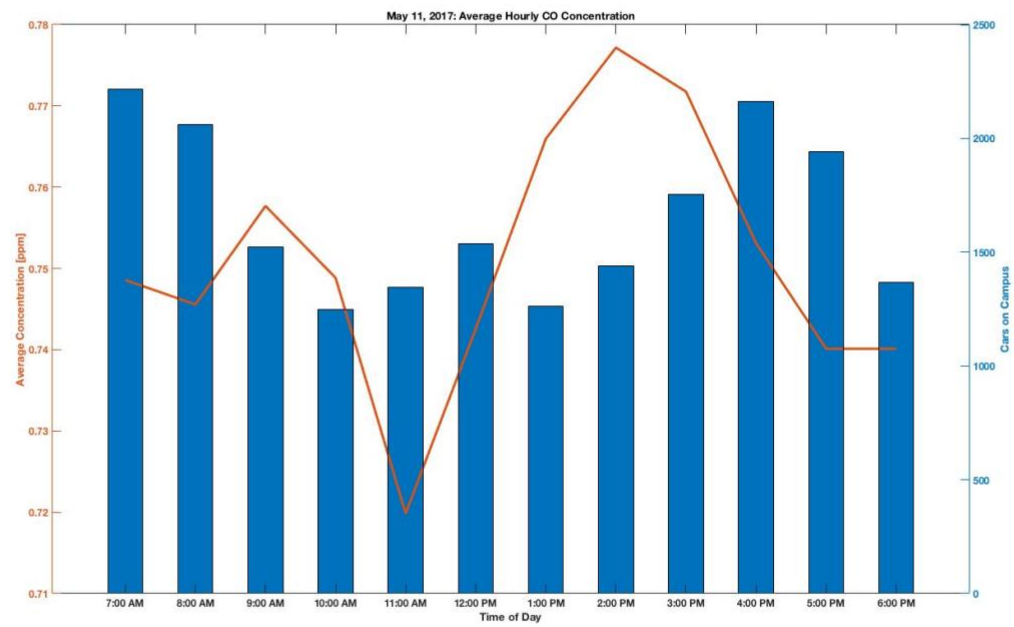


(b)

Figure 4.26: Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for May 11, 2017



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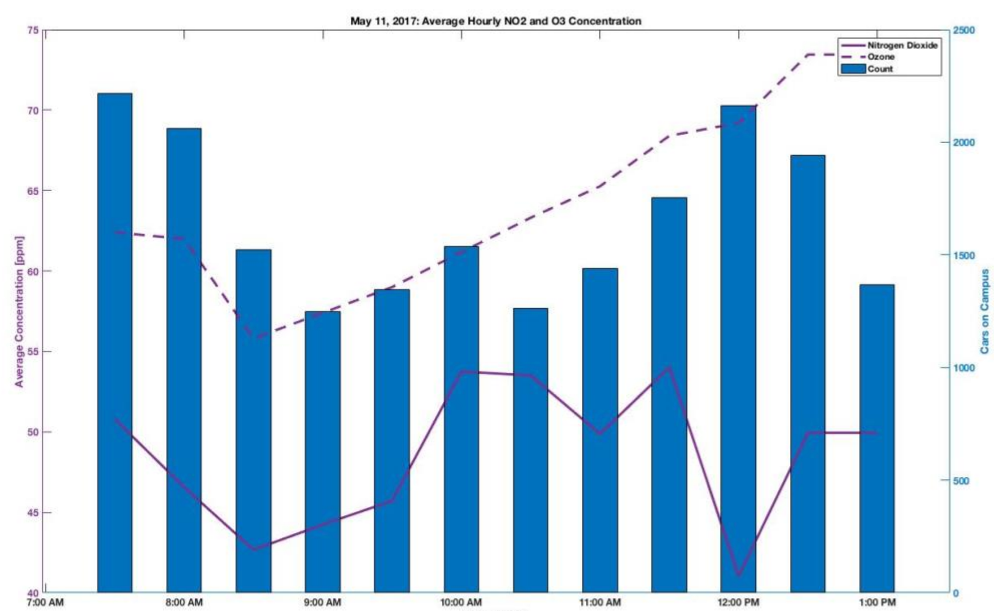


(b)

Figure 4.27: Average Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for May 11, 2017

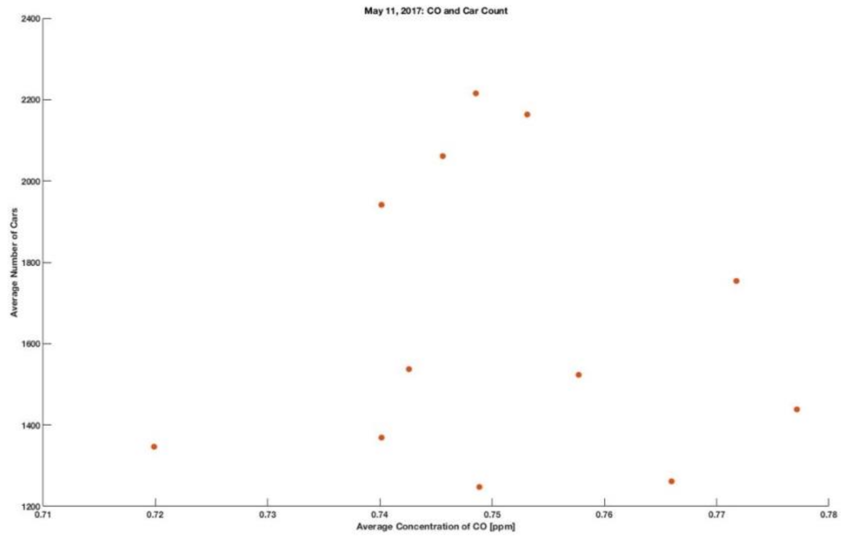


Figure 4.28: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for May 11, 2017

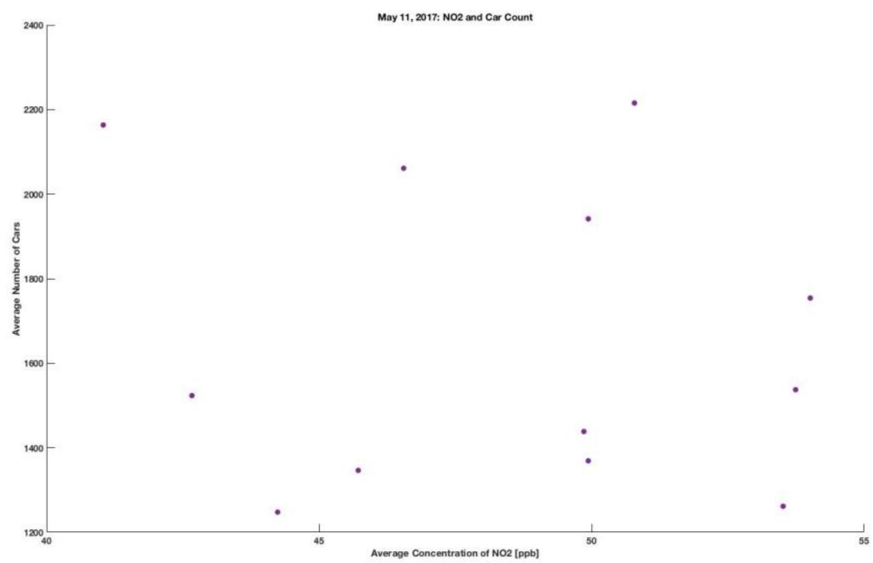


Figure 4.29: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for May 11, 2017

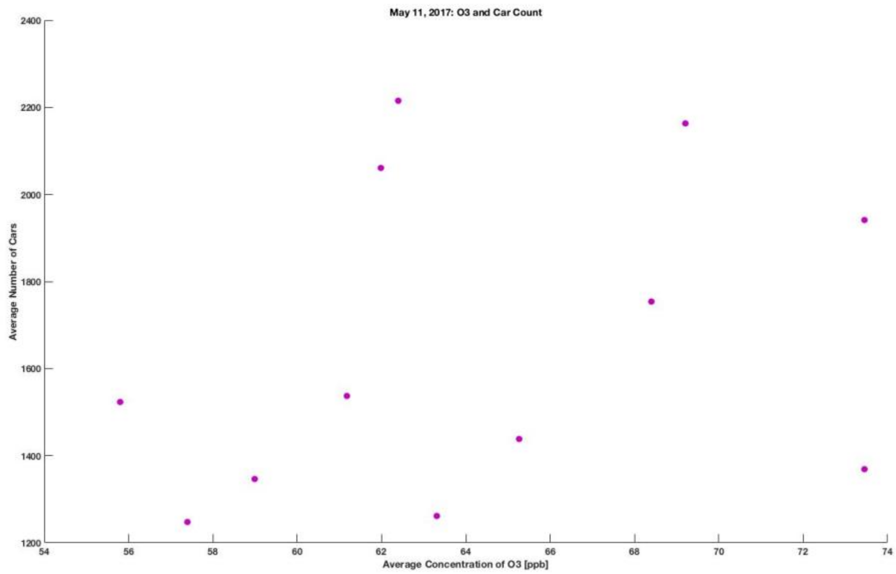
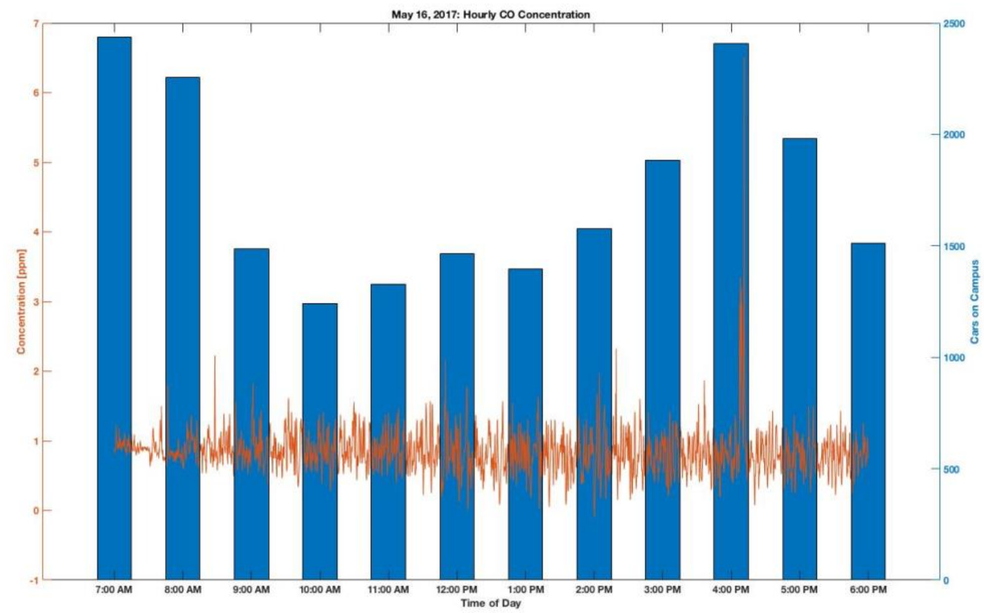


Figure 4.30: Average Hourly Ozone Concentration vs. Average Hourly Car Count for May 11, 2017



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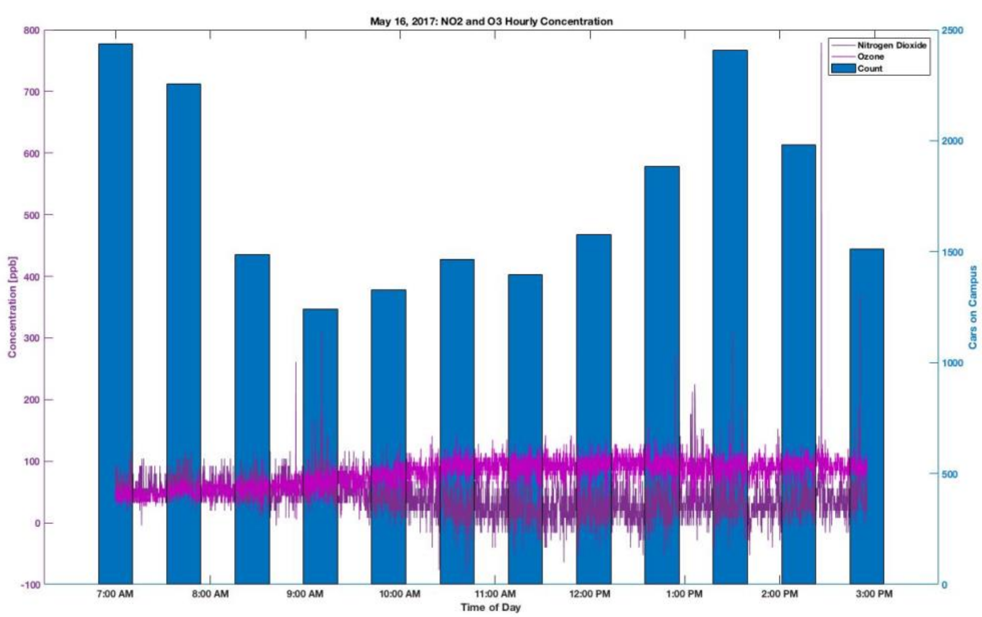

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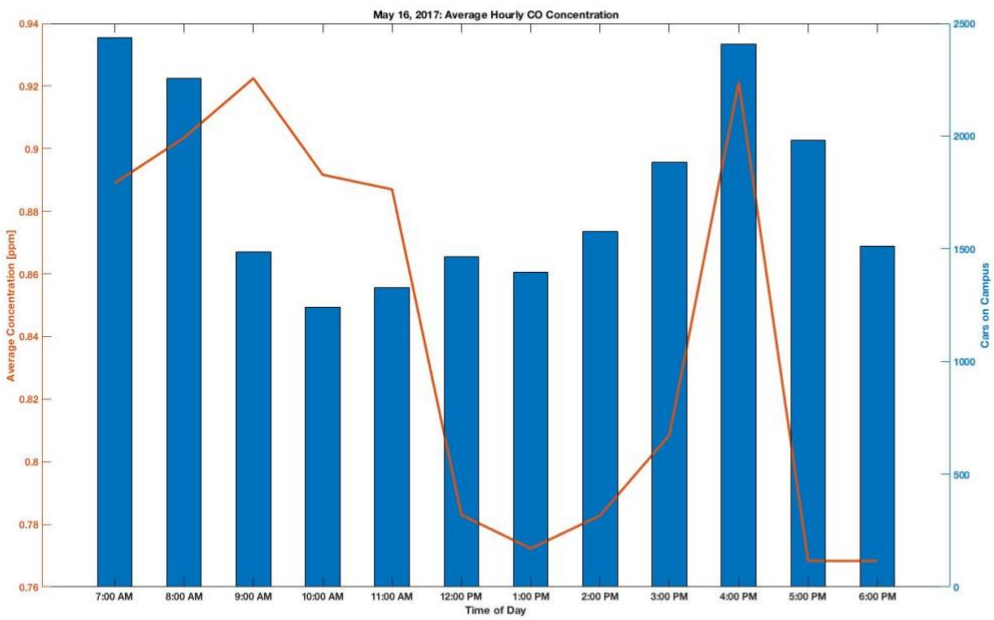
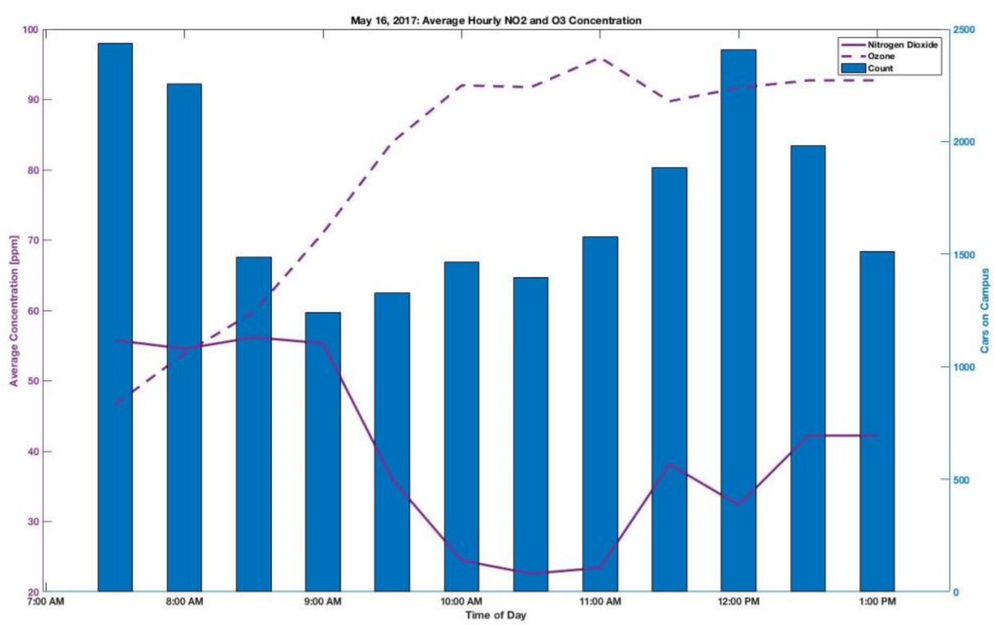
Figure 4.31: Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for May 16, 2017



(a)



(b)

Figure 4.32: Average Sensor Emissions of (a) Carbon Monoxide, (b) Nitrogen Dioxide and Ozone for May 16, 2017

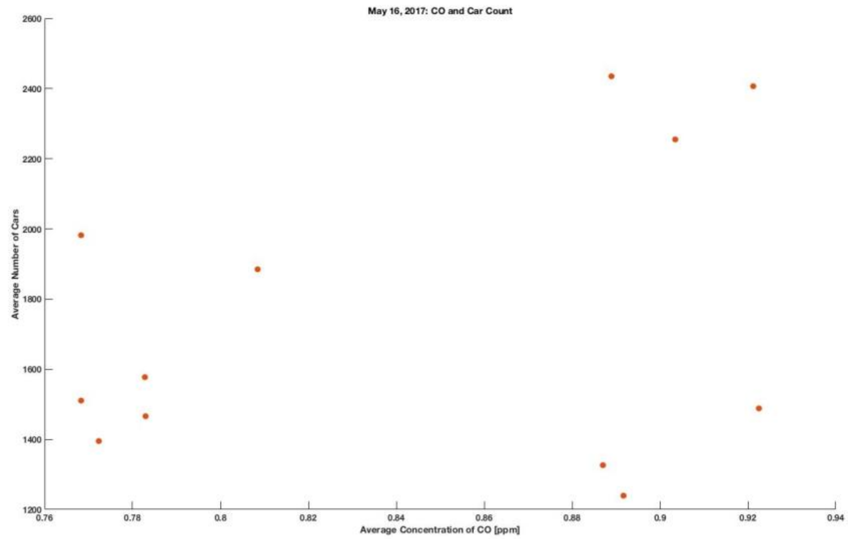


Figure 4.33: Average Hourly Carbon Monoxide Concentration vs. Average Hourly Car Count for May 16, 2017

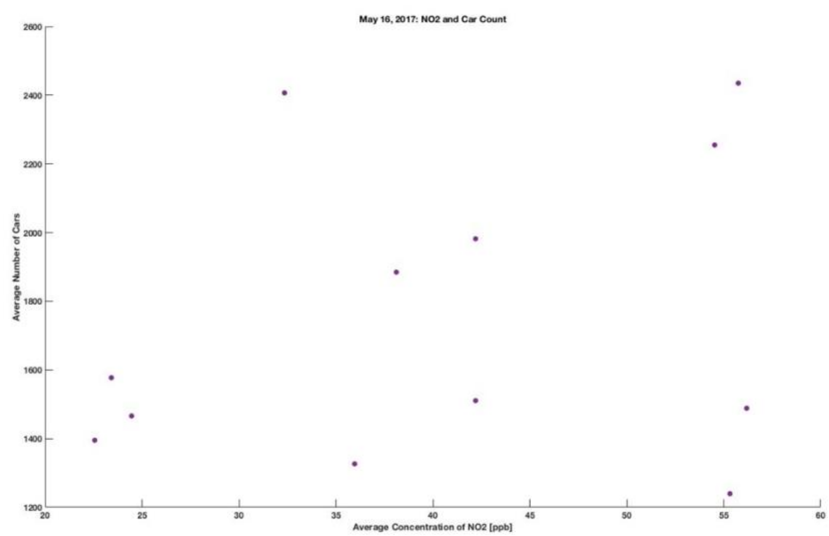


Figure 4.34: Average Hourly Nitrogen Dioxide Concentration vs. Average Hourly Car Count for May 16, 2017

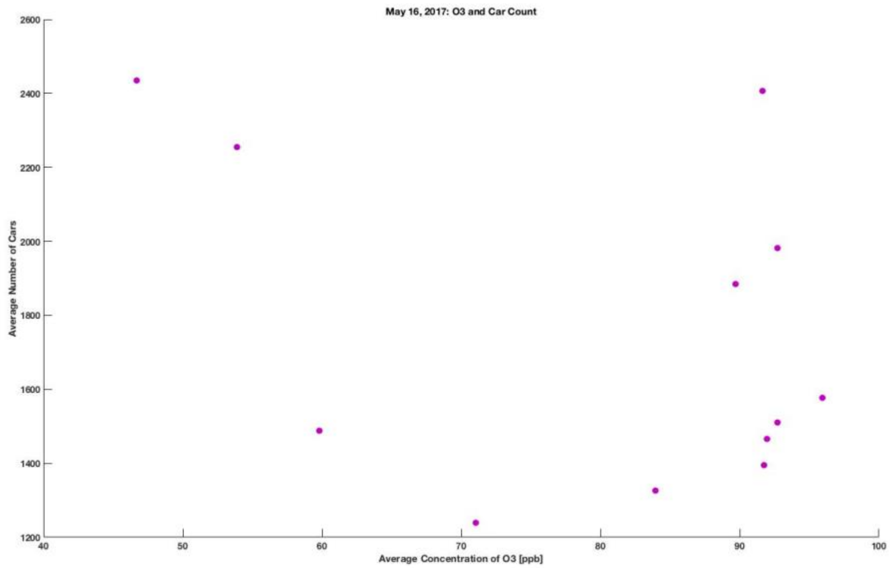


Figure 4.35: Average Hourly Ozone Concentration vs. Average Hourly Car Count for May 9, 2017

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